

2012

The Relationship Between Reading Coaches' Utilization Of Data Technology And Teacher Development

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THE RELATIONSHIP BETWEEN READING COACHES' UTILIZATION OF DATA
TECHNOLOGY AND TEACHER DEVELOPMENT

by

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A dissertation proposal submitted in partial fulfillment of the requirements
for the degree of Doctor of Education
in the College of Education
at the University of Central Florida
Orlando, Florida

Summer Term
2012

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ABSTRACT

The use of technology in assisting educators to use student data in well-devised ways to enhance the instruction received by students is gaining headway and the support of federal dollars across the nation. Since research has not provided insight as to whether or not reading coaches are using data technology tools with teachers, this mixed methods study sought to examine what behavioral intentions reading coaches have in using data technology tools with teachers, what variables may influence their behavioral intentions, and what trends may emerge in their views about using technology data tools with teachers.

A mixed methods approach was deployed via a survey embedded in an email, and data from 61 Florida reading coaches from elementary, middle, and high schools in a large urban school district were examined using an adaptation of the Technology Acceptance Model (TAM). The results showed that collectively all reading coaches have a high level of behavioral intentions towards using a data technology tool with teachers. The study also showed that elementary, middle, and high school reading coaches vary in their degree of behavioral intentions in using a data technology tool based on different variables. Trends in data showed that reading coaches think data technology tools are helpful, but that trainings are needed and that technology tools should be user-friendly. Discussion is provided regarding the implications of the study results for all stakeholders.

This dissertation is dedicated to the Northeast High School students in Dropout Prevention classes who changed my life. I spent just three consecutive days substitute teaching in their classes and as a result I gained a purpose: to become an educator.

ACKNOWLEDGMENTS

I am so grateful for the opportunities to learn that I have had at the University of Central Florida. It has been at this school that I have received wonderful support from faculty along the way. Dr. Timothy R. Blair, you have been there for me since my master's program and your support and humor have helped me get through two programs now, which is no small feat. Thank you for being my advisor and chair. I have learned so much from you and I am thankful for all of your wisdom, time, and efforts in developing me as an educator. Also, I was lucky enough to have had the best dissertation committee around in Dr. Vickie Cartwright, Dr. Jacquelyn Flanigan, Dr. Michelle Kelley, and Dr. Rosemarye Taylor. To my committee members: thank you for being there for me when I needed you. Dr. David Boote thank you for your unconventional thinking and for introducing ideas that helped me evolve as a student. Dr. Susan Wegmann, thank you for all of those great articles and discussions! Dr. Michael Hynes, thank you for your technology inspirations. To my cohort, especially Lee-Anne Spalding, thanks for the support, assistance, and connectedness along the way. Dr. Taylar Wenzel, I thank you for your encouragement, advice, and help while I've gone through this dissertation process. I am so grateful for the people of UCF and the light that they provided to my mind. Fortunately, I am extremely lucky to have had certain educators believe in me and provide me with opportunities to impact student success in my career as an educator and so special thanks goes to Patricia Smith, Sharyn Gabriel, James Larsen, Eric Hollinhead, Carmen "Diane" Knight, Ella Shanks, Dr. Michael Hynes, and Dr. Karen Biraimah.

Furthermore, I'd like to acknowledge my husband, Travis Behrens, as my number one supporter throughout this process. I am so grateful to have you in my corner! Additionally, this

educational journey would not be possible without the continuous support and encouragement of my family. You have always been there for me and I am so appreciative. Kris Hoekman, Joe Hoekman, and Rick Bourn, thank you for all of your help, support, and babysitting throughout this process. Bradley, only because you have been such a wonderful child have I been able to accomplish this goal. You are amazing! Kate, you have been onboard for this journey and an inspiration to me. Finally, Dr. Stephen Voss, thank you for believing in me. When I'm operating as an educator, I always think, "What would Dr. Voss do?"

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CHAPTER ONE: INTRODUCTION

The Problem and Its Significance

The concept of the use of technology for teacher development and student learning is receiving considerable attention in the educational community (Atkins et al., 2010; Greaves, Hayes, Wilson, Gielniak, & Peterson, 2010). Data technology tools hold promise for helping teachers understand, analyze, and utilize student data to promote more effective teaching and increase student learning (Gallagher, Means & Padilla, 2008). Reading coaches in our elementary and secondary schools are the individuals who assist classroom teachers in using data for the benefit of student achievement (Sturtevant, 2003). However, educational research has provided little guidance on whether or not teachers are being equipped and supported with data technology tools to improve student achievement (Borman & Feger, 2006). The present study addresses itself to the problem of how variance in data technology utilization is impacted by the behavioral intentions of reading coaches in public schools.

Conceptual Framework

Data-driven decision making has become the centralized focus of federal initiatives to positively impact student achievement. These federal initiatives, such as the Individuals with Disabilities Education Act (IDEA, 2004), No Child Left Behind legislation (NCLB, 2001), and Public Law 108-446, which introduced Response to Intervention (RTI), have required school districts and schools receiving federal dollars to analyze, disaggregate, track, and publically report student achievement data. This requirement has led to the wide-spread adoption and use of technology-based tools to assist in the processes required to analyze, disaggregate, track and report student achievement data (Mandinach, Honey, & Light, 2006).

Research, however, has indicated that the kinds of data technology tools teachers have access to do not typically help teachers connect student data to instructional actions and instructional resources (Gallagher et al., 2008). In fact in the *National Educational Technology Trends Study*, rarely did data systems incorporate model lessons, assessment data, and instructional materials aligned with curriculum that would benefit student achievement (Bakia, Yang, & Mitchell, 2008). Nevertheless, research has emerged to indicate some data technology systems or data tools are starting to gain use among teachers in helping them use their student data to drive instruction (Pinkus, 2009).

Teachers are expected to use data to drive instruction. Arne Duncan (2009), the current U.S. Secretary of Education, at the Fourth Annual Institute of Education Sciences Research Conference, stated “In the months and years ahead...we will ask millions of teacher to use student achievement and annual growth to drive instruction and evaluation” (Miller, 2009, p. 1). Having technology data tools available for teachers to use is important because research suggests that teachers, if left to break down and use their data without assistance, lack the training on how to make informed decisions based on data to help improve student achievement in the classroom (Means, Padilla, DeBarger, & Bakia, 2009). Furthermore, according to Miller (2009), research is indicating teachers oftentimes lack data literacy skills, such as comprehending data, interpreting data, finding trends in data, and using data efficiently.

In Florida, the web-based Florida Assessments for Instruction in Reading (FAIR) are given to students in grades 3-12 who may be struggling readers or at risk for developing reading deficiencies. Approximately 1.6 million Florida students in grades K-12 were assessed using the FAIR in the 2009-2010 school year (Keeler, 2010). The FAIR system uses a set of brief literacy

assessments to determine and report student literacy needs. FAIR provide educators with a large quantity of data that helps determine appropriate instruction. All teachers (science, mathematics, social studies, reading, etc.) can have access to their students' FAIR data because FAIR data are useful for instructing students in any academic setting.

The FAIR data are housed in an online data system called Progress Monitoring and Reporting Network (PMRN) that has various user capabilities which are outlined at <http://www.fcrr.org/FAIR/index.shtm>. User 1 is always a school principal and User 2 is always a reading coach or the school's reading contact. Teachers are trained by User 2 in how to administer the test and use data for instructional purposes. Anyone who has User 2 access also must be a FAIR Master Trainer, which means that User 2 has to have attended FAIR trainings and have passed a FAIR Master Trainer Test from the state making User 2 responsible for training the teachers at their school site. Furthermore, it is the responsibility of User 2 to create classes for teachers and give user access to teachers in order for teachers to gain access to their students' FAIR data ("Florida Assessments," 2009). Thus, reading coaches have significant responsibilities in determining how teachers will use the formative assessment data provided by the FAIR to impact student achievement at all Florida public schools. A challenge with FAIR, which is administered three times a school year, is the assessments generate massive amounts of data. Teachers using FAIR may experience difficulties in using the data for instructional purposes without the help of data technology tools. Research from Bakia, Yang, and Mitchell (2008) shows that when teachers do have access to data, like FAIR data, that there typically is "a lack of instructional tools to help teachers act on the data provided to them" (Bakia et al., 2008, p. viii).

It is clear that teachers are the most important individuals when it comes to impacting student achievement (Mandinach et al., 2006). Schools where students are showing unusual academic gains are directly connected to the intentional and well-devised ways that student data was used to deliver instruction aimed at positively impacting student achievement (Mandinach et al., 2006). Additionally, formative assessment “is the only type of data use that has been shown to increase student achievement” (Miller, 2009, p. 5). Since FAIR data are formative assessment data, the need for data technology tools that can help teachers use the FAIR data for classroom application in well-devised ways becomes all the more apparent. Nationally, reading coaches are seen as instructional leaders at schools to help teachers access, interpret, and utilize data to impact instruction for the benefit of improving student literacy skills and increasing student achievement (Sturtevant, 2003). In Florida, reading coaches are the instructional leaders charged with helping teachers understand and utilize FAIR data. Reading coaches in Florida have an important role as data experts because FAIR data have the potential to help teachers to impact student achievement.

Reading coaches play a key role in school improvement, a role that has evolved over time. The first mention of job responsibilities usually associated with reading coaches nowadays first began in the 1920’s (Hall, 2004). More officially, in 1965 the Elementary and Secondary Education Act (ESEA) allocated federal funds for “Title I Teachers” to pull out and work with struggling readers in small groups (Dole, 2004). Often, these teachers were reading specialists. In 1998, the Reading Excellence Act by President Clinton began providing federal funding towards reading initiatives. In 2001, however; the most headway was seen in taking the role of reading specialist, giving it new focus and a new name “reading coach” when the federal

initiative No Child Left Behind introduced the Reading First Initiative (Dole, 2004). Both of these initiatives provided funds that were designed to improve reading instruction and in many cases schools used the funding provided to employ reading coaches (IRA, 2004). The role of the reading coach differed in some ways from the reading specialist role, in that reading coaches were seen as specialists who worked with teachers in improving their instructional abilities instead of working with small groups of children (Dole, 2004). The International Reading Association (IRA) (2004) introduced a position statement regarding the role of the reading coach, which also detailed desired qualifications. The IRA explains that reading coaches have a leadership role that involves being a reading specialist; therefore, morphing the two roles into one. A reading coach has multiple jobs that include improving the practice of teachers in the classroom by teaching model lessons, co-teaching lessons, creating conversations focused around student learning, making and providing professional development, visiting classrooms, etc. Relevant to this study, reading coaches also have a role in assessment. Specifically, a part of a reading coach's job is to educate and guide teachers in how to utilize student data in order to create optimal instruction. In fact, the IRA states that a role of the reading coach includes, "interpreting assessment data (helping teachers use results for instructional decision making)" (IRA, 2004, p. 3).

The Importance of Literacy Skills

A prerequisite for success in life is having the ability to read. According to research, reading is an imperative skill that will determine how most individuals advance in society, socially, and economically (Snow, Burns, & Griffin, 1998). The national average for high school dropouts is 1.2 million students annually or roughly 7,000 students dropping out every school day,

which is equivalent to one out of every three students in school becoming a dropout statistic (Balfanz, Fox, Bridgeland, & McNaught, 2009; “The High,” 2009; “National Commission,” 2008). A student is at risk for dropping out of high school when demonstrating below grade level reading abilities (Balfanz et al., 2009). Additionally, U.S. cities that have the highest levels of poverty and crime have been found to have increased high school dropout rates (Balfanz et al., 2009). Alarming, a common characteristic of adults who live in poverty or are incarcerated is that they lack in basic literacy skills (Kutner, Greenberg, Jin, & Paulsen, 2006; Greenberg, Dunleavy, & Kutner, 2008). High school dropouts are also likely to be dependent on financial assistance from the government to sustain their wellbeing and survive (“The High,” 2009). Furthermore, a student who drops out of high school is predicted to make roughly \$8,000 less money annually than a high school graduate and have employment interruptions throughout their lives. Research indicates that individuals without a high school diploma are the hardest hit when the economy drops in experiencing lost jobs (“The High,” 2009). Unfortunately, the children of high school dropouts are more likely to drop out of school too; perpetuating a cycle of poverty, incarceration, and unemployment (“The High,” 2009). *The Silent Epidemic: Perspectives of High School Dropouts* (2006) provides recommendations for keeping students from dropping out of high school and one prominent recommendation is to provide struggling students with opportunities to improve their literacy skills.

Providing struggling readers with opportunities to improve their literacy skills are key and the impact of literacy on one’s quality of life are profound. According to the *Education for All Global Monitoring Report* (2006), the benefits of being literate include

political, cultural, and social aspects. Politically, people who have literacy skills are better positioned to participate and contribute to a democracy. Culturally, literacy skills influence the degree to which an individual makes decisions about their culture in preservation or changes. Socially, literate individuals are more likely to have better health for themselves and their children as well and see that their children are educated.

It is obvious that literacy is key in promoting the success and well-being of students in schools today and their future generations. It is therefore to the benefit of each individual student, their future generations, and society to implement public education that provides students with the best possible reading education which begins with individual teachers in grades K-12 and includes reading coaches, who can positively impact the quality of instruction students receive from teachers day-in and day-out.

Purpose of the Study

The purpose of this study is to investigate behavioral intentions reading coaches have in using a data technology tool with teachers. According to Davis (1989), Venkatesh and Davis (2000), and Venkatesh (2000) behavioral intentions predict system use. Hypotheses advanced are:

1. Reading coaches have specific behavioral intentions when utilizing a data technology tool with classroom teachers.
2. Reading coaches utilize a data technology tool with classroom teachers based on different behavioral variables.

3. There is a difference in the relationships between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers for elementary, middle, and high school levels.
4. Reading coaches will have similar opinions regarding the utilization of data technology tools with teachers.

First, it is hypothesized that reading coaches have specific behavioral intentions when utilizing a data technology tool with classroom teachers. This first hypothesis is based on the Technology Acceptance Model (TAM) Theory which indicates that individuals have specific behavioral intentions to use technology (Davis, 1989; Venkatesh & Davis, 2000). The research question that pertains to this hypothesis is, What behavioral intentions do reading coaches have when utilizing a data technology tool with classroom teachers?

The second hypothesis states that reading coaches utilize a data technology tool with classroom teachers based on different behavior variables. Research by Davis (1989) and Venkatesh and Davis (2000) proposed that variables such as perceived usefulness, perceived ease of use, computer self-efficacy skills, and subjective norms influence the behavioral intentions individuals have in using technology. This hypothesis seeks to answer the research question, To what extent do reading coaches utilize a data technology tool with classroom teachers based on different behavioral variables?

The third hypothesis is a belief that there is a difference in the relationships between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers for elementary, middle, and high school levels. The hypothesis is connected to the research question, Is there a relationship between reading coaches' behavioral intentions and

utilization of a data technology tool with classroom teachers reflected identically at the elementary, middle, and high school levels?

The fourth and final hypothesis is that reading coaches will have similar opinions regarding the utilization of data technology tools with teachers. This hypothesis qualitatively examines the question: What are reading coaches thoughts on using data technology tools?

Operational Definitions

1. Adequate Yearly Progress (AYP)-AYP refers to the way student achievement is measured yearly at each school that receives federal dollars. AYP is reported into subgroups, which include, for example: white, black, economically disadvantaged, etc. AYP is mentioned because schools have to report out AYP in order to receive federal dollars and AYP data can be tracked in the Teacher Data Tool.
2. Florida Assessments for Instruction in Reading (FAIR)-The FAIR system uses a set of brief literacy assessments to determine and report student literacy needs. The FAIR provides educators with data that helps determine appropriate instruction. For the purpose of this study, any mention of the FAIR is referring only to the computer adaptive assessments given to students in grades 3-12 that are web-based. Students in grades K-2 also take the FAIR, but not the same web-based version taken by students in grades 3-12.
3. FAIR reading profiles-The FAIR reading profiles are determined by three scores on the FAIR, which include the Reading Comprehension, Maze, and Word Analysis scores. The FAIR reading profiles reflect student needs regarding curriculum and recommended strategies that may assist a student in each respective profile. Every student who takes the FAIR will have a FAIR reading profile. There are five FAIR reading profiles students can score into and these include

box 1, box 2+4, box 2+5, box 3+4, and box 3+5. Student progress can be monitored by the FAIR reading profile a student's scores generate over the three FAIR assessment periods per school year. Box 1 is the highest scoring reading profile followed in descending order by box 2+4, box 2+5, box 3+4, and box 3+5.

4. FAIR quick-links and modules-The district-adopted FAIR quick-links and modules are documents with correlating videos and strategies that provide educators with streamlined resources for each of the FAIR reading profiles. The FAIR modules also explain the state-adopted reading tool that is embedded in the Teacher Data Tool, the Teacher Data Tool, and specifically link to the Informal Diagnostic/Progress Assessment for Grades 3-12 Tool Kit for each FAIR reading profile. The FAIR quick-links and modules were developed by the researcher, district reading specialists, district RTI specialists, and reading coaches.

5. Informal Diagnostic/Progress Assessment for Grades 3-12 Tool Kit –The kits contain further pencil and paper assessments that can be given to students depending on their FAIR reading profiles, if more data are needed. The kits also contain teaching resources.

6. Teacher Data Tool-The district-adopted tool, created for educators by the researcher and her husband, utilizes FAIR data. The tool allows teachers to progress monitor student achievement, input teaching actions, and graph student fluency scores over time. The purposes of the tool are to help teachers actively use FAIR data to shape instruction in a flexible manner which is intended to positively impact student success and promote reflective, action-oriented teaching. Importantly, this tool received a positive review by educators at the Florida Department of Education. In the survey the Teacher Data Tool is referred to as the Teacher Progress Monitoring Tool for FAIR.

7. Reading Certification-A master's degree in reading education or at least 30 semester graduate-level hours in reading and a passing score on the state Reading Subject Area Test. Reading certified teachers can teach reading in grades K-12.
8. Reading Coach-A reading coach is the primary individual at a school site responsible for providing professional development, coaching, and support to teachers in understanding, interpreting, analyzing, and using data. In Florida, reading coaches help teachers use FAIR data for the intention of bettering student literacy skills and promoting student achievement. Reading coaches may sometimes be referred to as "coaches" in this study.
9. Reading Contact-In lieu of a reading coach, a reading contact (usually an individual who is a resource teacher with the assigned duties of a reading coach) is the primary individual at a school site responsible for providing professional development, coaching, and support to teachers in understanding, interpreting, analyzing, and using FAIR data for the purpose of bettering student literacy skills and promoting student achievement. In this study, "reading contacts" will be called "reading coaches" since they have the responsibilities of reading coaches regarding the use of FAIR data by teachers.
10. Reading Endorsement-300 hours of reading courses through a district or 15 college-level semester hours in reading. This endorsement allows educators to teach reading in grades K-12.
11. Subjective Norms- Subjective norms refer to people's perceptions that important others think they should or should not engage in a said task.
12. Technology Acceptance Model (TAM)-The Technology Acceptance Model was developed to predict usage of technologies.

CHAPTER TWO: REVIEW OF LITERATURE

The purpose of this study is to ascertain how reading coaches assist teachers in utilizing data technology tools for the purpose of providing students with impactful instruction. Reading coaches are hired to optimize the effectiveness of teachers and how they instruct students. A part of reading coaches' jobs is to educate and guide teachers in how to utilize student data in order to create optimal instruction (IRA, 2004). The literature review will highlight the benefits of using data technology tools to shape student data in ways that are useful in helping teachers plan strategic instruction for students. Additionally, research will be reviewed suggesting the need for teacher technology tools that will help teachers reflect on data, quickly organize data, identify trends in data, progress monitor student achievement, and make decisions based on student data to improve the quality of instruction students need to receive in order to be successful. The review of literature will further indicate the importance of a reading coach's role in assisting teachers in the use of data to drive instructional decision-making and the role data technology tools may play in assisting educators in their endeavors to positively affect student achievement.

The Role of Assessment

According to the International Reading Association, testing students to determine their knowledge and skills is "an important part of education" (IRA, 1998, p. 2). Furthermore the International Reading Association (1998) reports that assessment data helps provide educators with information that has the potential to guide impactful instruction. Thus, a student's reading achievement is most likely to be positively affected by a teacher who uses student assessment data to create appropriate reading instruction tailored to the student's needs (Heilman, Blair, & Rupley, 2002). The National Council on Teacher Quality (2012) found that in a typical school

year teachers make approximately 11,000 important decisions regarding the instruction students receive. Hence, informed decision-making based on student data becomes all the more important in helping students increase their reading abilities because without informed decision-making “literacy instruction can be irrelevant...for all concerned” (Heilman et al., 2002, p. 35).

Teacher effectiveness in reading instruction is a significant determinant in impacting student achievement (Heilman, et al., 2002). Teachers are a crucial factor in affecting student learning because they are the ones who have interactions with students (Wayman, Cho & Johnston, 2007). In fact, when student achievement data are used by teachers to shape teaching based on student needs, there can be a positive outcome of increased student achievement (Black & Williams, 1998). Schools that are successful in attaining the positive assessment results of children attribute success to assessment used in ways to promote student learning by classroom teachers (Roehrig, Duggar, Moats, Glover, & Mincey, 2008; Lezotte, 1991). Furthermore, Roehrig et al. (2008) indicated assessment that is frequent in nature and used to provide guidance on instructional changes is powerful in positively affecting the achievement of struggling readers. Assessment has historically been a driving force in helping teachers provide good reading instruction.

History of Reading Assessment

In the 1880s reading assessment was informally conducted by teachers through observations of the written and oral performances of students (Tierney, Moore, & Valencia, & Johnston, 2000; Sableski, 2008). In 1901 the U.S. National Bureau of Standards, made the recommendation for standardized reading assessments (Tierney et al., 2000). Thus, norm-referenced assessments and standardized tests that measured oral and silent reading level became

popular between 1910-1930 (Sableski, 2008). Students during this time were required to read unfamiliar passages and respond to questions to determine comprehension (Tierney et al., 2000). In 1917 Thorndike produced one of the first attempts to measure a person's reading comprehension abilities in his article called "Reading as Reasoning." In "Reading as Reasoning," Thorndike theorized the thought processes that he assumed must lead to reading comprehension (Sarroub & Pearson, 1998). Thorndike believed that assessment was instrumental in determining whether or not teaching instruction was working in improving student achievement (Sableski, 2008). From approximately 1910 to the late 1940s various kinds of assessment flourished, including short answer responses, bubbling in answers, essays, and debate-like activities in measuring reading comprehension (Sarroub & Pearson, 1998). Beginning in the 1940s informal reading inventories emerged and evolved as time moved forward to eventually include oral miscue analysis, which was introduced by Goodman and Burke in the 1970s (Sarroub & Pearson, 1998). Unlike formal assessment, informal reading inventories helped teachers pinpoint student reading needs so teachers could provide more impactful instruction. Later, in the late 1960s criterion-referenced assessments emerged as a way of gauging mastery of content taught (Sarroub & Pearson, 1998). Consequently, criterion-referenced assessments began appearing in the basals of the 1970s and 1980s (Sarroub & Pearson, 1998; Sableski, 2008). Then in 1969 Title One reauthorization heralded in an accountability movement that has continued to have a lasting impact on accountability measures of student achievement nationwide and the movement was also the impetus of state assessments (Sarroub & Pearson, 1998). The theory that whatever was assessed would become what teachers would focus their instruction on soon took root with state assessments where student data became shared information for stakeholders (Smith, 2002).

While standardized assessment gained headway in the 1970s, other kinds of classroom formative assessments, in addition to the informal reading inventories, become more prevalent including think alouds (where students shared their thinking processes while trying to understand text) and retelling. In the late 1970s Durkin's landmark study revealed that comprehension was being assessed, but not taught (Durkin, 1978). Her study impacted how teachers prepared students to comprehend text and was the catalyst for more comprehension focused instructional practices making headway into classes across the nation (such as reciprocal teaching and graphic organizers) (Sarroub & Pearson, 1998). The impact of Durkin's landmark study is still felt in classrooms today. While formative assessment and comprehension focused instruction were moving along in tandem, the 1980s and 1990s briefly saw a decline of interest in criterion-referenced assessment; however, currently criterion-reference assessments have come back into the limelight (Sableski, 2008). The 1980s and 1990s also saw an increase of the use of portfolios as a measure of formative assessment used by classroom teachers (Sarroub & Pearson, 1998). Currently, norm-referenced assessments where student achievement can be compared nationally have swept the nation (Tierney, et al., 2000). Sableski (2008) noted that reading assessment will continue to evolve based on the ever-changing definition of reading, kinds of literacies, and the values of society. It is apparent that assessment and instruction have a close relationship that is both dynamic and interdependent in impacting student reading abilities.

Historical View of Reading Coaches

Reading coaches are an essential ingredient to school reform and federal dollars have been allocated to ensure that schools have the opportunity to reap the benefits of having a site-based reading coach (IRA, 2004). Research on coaching emerged with the work of Joyce and

Showers (1982) when they presented a peer coaching model that involved teachers coaching teachers. The research of Joyce and Showers (1982) eventually showed that teachers who worked with other teachers in a coaching model utilized new best practices and strategies as opposed to teachers who did not participate in a coaching model. This breakthrough research opened the eyes of educators and policy holders nationally to the power of having a coach work with teachers to improve student achievement.

The Reading Excellence Act of 1998 and the No Child Left Behind federal legislation of 2001, which introduced Reading First, were instrumental in promoting reading as a national priority and reading coaches as a part of the solution to the literacy epidemic in the United States (Dole, 2004; IRA, 2004). Dole, Liang, Watkins, and Wiggins (2006) found in their data collection across 48 states that when the term “reading coach” was brought up it was associated with Reading First, another indicator of the effects of federal legislation, and especially the Reading First Initiative. As a mandatory component of Reading First, states have spent huge amounts of their literacy initiative budgets to fund reading coaches in schools (Snow, Ippolito, Schwartz, 2006). For example, 31 million dollars was allocated to fund reading coaches in Pennsylvania by the Annenberg Foundation and Florida dedicated over 30 million of its 90 million dollar literacy initiative budget for reading coaching (Snow et al., 2006).

Reading coaches were mandated in schools servicing students in grades K-3; however, it is well-noted that the success in those grades related to coaching prompted states to also allocate funds for secondary reading coaches where sometimes there seems to be less hope for students struggling with reading to experience success (Snow et al., 2006). The presence of reading coaches in secondary schools, where students who are struggling readers are at a high risk for

dropping out of school, indicates the importance of a reading coach role as a beacon of hope (Balfanz et al., 2009). Overall, reading coaches are an important part of school reform and many times are federally funded or district funded positions based on the need for such change agents in schools (Nelsestuen, Hanita, Robinson, Coskie, & Regional Educational Laboratory at Education Northwest, 2009).

Reading coaches have multiple responsibilities associated with their position. One such role is in helping teachers utilize student data to improve and strategize the instruction provided for students in the classroom. Reading coaches are typically former teachers who were successful at their jobs as teachers and therefore are considered to be skilled enough to improve the instructional practices of other educators (Sturtevant, 2003). According to a study by the National Center for Education Evaluation and Regional Assistance, 73% of new and experienced elementary teachers felt that reading coaches aided them with utilizing their data (Nelsestuen et al., 2009).

Importantly, reading coaches are seen as critical instructional leaders at schools to help teachers access, interpret their data, and utilize data to impact instruction for the benefit of improving student literacy skills and increasing student achievement. Reading coaches help teachers plan their instruction by using data (Walpole & Blamey, 2008). Furthermore, reading coaches are instrumental in assisting teachers in determining if their instructional strategies and practices are working by guiding them in progress monitoring their data and by coaching them on other strategies that may work better when data shows their current practices are not working (Walpole & Blamey, 2008). However, research has not provided guidance on whether or not reading coaches, who are typically former teachers, have the necessary skills to help teachers

utilize data tools for the purpose of promoting student success (Sturtevant, 2003); therefore, research will be examined regarding the technology acceptance of reading coaches in utilizing data technology tools with teachers.

Reading Coaches' Relationship to Classroom Teachers

Reading coaches are thought to be change agents in schools. The Reading First Initiative promoted reading coaches as key to promoting stronger teaching capacities of teachers (Dole, 2004). In one meta-analysis it was found that “Teachers credit their coaches with helping them try new practices, incorporate more authentic assessments, ground their decisions in professional literature, and create curriculum that was more student-centered” (Vanderburg & Stephens, 2010, p. 1). In the same meta-analysis teachers were reported as thinking the value of coaches was most relevant in data analysis, test administration, and modeling lessons. According to research reported by the U.S. Department of Education, teachers feel that coaches improve their teaching practices and open them up to trying new ideas (Deussen, Coskie, Robinson, & Autio, 2007). This research echoes the initial research findings of Joyce and Showers (1982). Elish-Piper and L’Allier (2010 and 2011) reported research that shows teacher literacy environments are more enhanced by teachers who have worked with coaches than those who have not. A study conducted by Bean, Draper, Hall, Vandermolen, and Zigmond (2010) found that teachers had a more positive view of coaches that deepened as coaches spent more time with teachers. Finally, in a case study conducted by Coburn and Woulfin (2012), reading coaches had more of an influence on the instructional practices of teachers than principals or district and state leaders; a compelling finding that deserves more attention and study.

Reading Coaches and Student Achievement

According to the *Handbook of Reading Research* (2011), there is little empirical evidence regarding the effects reading coaches have on student achievement. However, there are some studies that indicate positive findings regarding reading coaches' impact on student achievement. For example, in a study of Florida middle school reading coaches, Marsh et al. (2008) reportedly found that student achievement was higher in schools where reading coaches were allocated more time in analyzing and using student data with teachers. L'Allier, Elish-Piper, and Bean (2010) reported in two separate studies on reading coaches that when reading coaches spend time with teachers, student achievement is higher. Walpole and Blamey (2008) linked schools with higher AYP scores as being schools that have reading coaches compared to schools without reading coaches.

Several studies reported in the U.S. Department of Education funded guide *Reading First Coaching: A Guide for Coaches and Reading First Leaders* (2004), provided evidence that reading coaches are associated with positive student achievement. These studies involved the Foundations for California Early Learning model, a study by Lyons and Pinnell (1999) which found a positive relationship between reading coaches and student reading and writing achievement; Norton's (2001) research regarding a reporting from the Alabama Reading Initiative that reading coaches contributed to the significant growth of student achievement; and a California study reported by Lapp, Fisher, Flood, and Frey (2003) that reported student reading achievement connected to reading specialists endeavors to provide part-time peer coaching and part-time student tutoring for students from three low socioeconomic schools. A study by Swartz (2005) revealed that students in grades K-4 showed reading gains that were attributed, in

part, to the involvement of reading coaches. Finally, Bean et al. (2010) reported in their research that there was a significant correlation between student achievement and schools where coaching occurred often. Their study examined twenty reading coaches in Pennsylvania Reading First Schools through interview analysis and by examining student data.

Overall, the research is pointing to reading coaches having positive effects on student achievement. Importantly, a study by Blachowicz et al. (2010), interviews revealed a trend that hundreds of educators, including principals, district leaders, teachers, and others felt that “the coach’s effect on the instruction and infrastructure of the school emerged as one of the top three influences for change cited by all participants” (Blachowicz et al., 2010, p. 348).

Professional Development for Reading Coaches

Reading coaches were hired to provide long-term professional development at school sites as a way to extinguish one-shot professional development that teachers were receiving at schools across the nation. In this light, it is recommended that reading coaches also receive long-term professional development (Deussen et al., 2007; Blachowicz et al., 2010; Stephens, et al., 2011).

Not until 2005, however did the National Center for Reading First Technical Assistance provide “Leading for Reading Success: An Introductory Guide for Reading First Coaches,” to assist coaches (Deussen et al., 2007). Prior to 2005 most reading coaches were doing the best that they could, allocating their own resources for professional development and relying on other professionals for development (Deussen et al., 2007). Deussen et al. (2007) reported that state level and district level trainings did commence thereafter and many districts offer monthly coach trainings and/or summer professional development opportunities for coaches (Deussen et al.,

2007). Additionally, many states provide reading coaches with reading improvement plans, checklists, and to-do lists to aid them in their roles.

Marsh et al. (2008) argued that reading coaches need on-going professional development in order to coach others effectively. The authors further contend that this ability to help teachers to continually grow professionally can only happen by continuing the professional development of reading coaches. Reading coaches are expected to have a strong foundation of specialized knowledge to layer their on-the-job professional development upon. In fact, reading coaches are recommended to have more specific knowledge and it is suggested by the IRA (2004) that reading coaches have a master's degree with a specialization in reading that leads to reading certification, intensive year-long professional development in reading provided by a school district, or participate in other reading-focused programs. Two studies by L'Allier and Elish-Piper (2006) and Elish-Piper and L'Allier (2007) indicate that a strong reading background does make a difference in the quality of a reading coach and their abilities to impact student reading achievement. Dole (2004) points out that reading coaches need to be more knowledgeable and skilled than the teachers they are working with at schools. Furthermore, professional development must be experienced in an on-going manner by coaches.

However, the content of the professional development recommended for reading coaches is sparingly mentioned. Blachowicz et al. (2010) report that coaches are at different levels of knowledge and skill and would benefit from differentiated instruction in terms of professional development, but guidance on what should be learned by the reading coaches is not mentioned.

Research lacks a clear picture of the professional development reading coaches are receiving. Overall, it appears that reading coaches may benefit from professional development centered on

data analysis tasks since teachers are indicated to have a need in this area and considering that reading coaches are typically former teachers, they may need to grow their knowledge in the area as well.

Florida Reading Coaches

September 7, 2001 was a significant day for the State of Florida as governor Jeb Bush heralded in Florida's reading initiative as reported by the Just Read Florida website at <http://www.justreadflorida.com/>. As a result, Florida showed a dramatic increase of reading coaches as it embraced Reading First implementation. In fact, reading coaches ranged from 318 in the 2002-2003 school year (the year reading coaches were designated roles in Florida schools) to approximately 2,441 coaches in the 2009-2010 school year as reported by districts' K-12 Comprehensive Reading Plans found at https://app1.fldoe.org/Reading_Plans/ (Miller, 2010). Furthermore, Florida statute 1001.215, recommends school systems, "Train highly effective reading coaches."

Florida tracks the time coaches spend in various designated areas by using a reporting log that each coach enters into in the Progress Monitoring and Reporting Network (PMRN) system. The 13 areas that represent where the time coaches spend are: whole faculty professional development, small group professional development, planning, modeling lessons, coaching, coach-teacher conferences, student assessment, data reporting, data analysis, meetings, knowledge building, managing reading materials, and other. The "other" category includes responsibilities not related to the job of coaching, such as bus duty, lunch duty, etc. (Marsh et al., 2008; Miller, 2010).

It is the expectation of the State of Florida that reading coaches spend at least 75 percent of their time in five areas, including providing small group professional development, modeling lessons, coaching, holding coach-teacher conferences, and data analysis. The State of Florida put an emphasis on the coaches' role as data experts (Miller, 2010). Interestingly, when the state examined their data for the 2009-2010 school year, none of the five regions of Florida were spending 75% of their time on the expected five areas (Miller, 2010). The state average showed that reading coaches were spending only 39% of their time in the five areas (Miller, 2010). These actual percentages in the five areas only add up to slightly more than half of the 75 percent of time expected for these areas. Most of the regions reported spending only about 6%-7% of their time analyzing data (Miller, 2010). This percent of time would be less than two hours a week approximately, which is much lower than the national average indicating approximately five hours per week is spent on tasks related to analyzing data as reported by the IRA in a 2006 survey (Bean, Draper, Hall, Vandermolen, & Zigmond, 2010). Another study by the U.S. Department of Education (2007) found that coaches spent 25% of their time working on data-analysis activities. These statistics indicate a large difference in how much time Florida reading coaches engage in data analysis activities compared to reading coaches nationally.

A major question asked at the Florida Reading Association Conference during a presentation by Miller (2010) was, "What do you believe to be the barriers to coaches using their time most effectively?" A reason this question was posed is that the Florida reading coach PMRN logs are indicating that reading coaches are not spending enough time analyzing data and having discussions with teachers about how to use data constructively in classrooms (Miller, 2010). Florida reading coaches feel that time is a barrier to their effectiveness as coaches

(Roehrig et al., 2008). The possible positive impact of reading coaches in schools is lessened when they are assigned to unrelated “other” duties, which are in direct opposition to the state’s guidelines (Marsh et al., 2008). Thus, Florida reading coaches frequently have disruptions in their days that take them away from their roles as change agents at schools. It becomes apparent, that reading coaches may not have the time they need to work with data to have valuable discussions with teachers that can impact student needs in the classroom. Marsh et al. (2008) reported lack of time as a key roadblock , especially when “we found higher student achievement in schools where coaches spent more time working with reading teachers to analyze and use student data” (Marsh et al., 2008, p. 504). Thus, finding the time for reading coaches to work with teachers in analyzing and using student data is important, and when this practice is limited or not happening frequently it seems that missed opportunities to improve student achievement may be occurring. Despite time being of key concern, the authors sparingly mentioned ideas for creating ways for reading coaches to be able to orchestrate this aspect of their jobs. The authors did suggest that administrators and policy makers attempt to find solutions that would involve finding more time for reading coaches to spend time in classrooms (Marsh et al., 2008). The authors do note that “To support this data analysis and support role, administrators should continue providing professional development for coaches in this area, with a particular focus on responding to these results” (Marsh et al., 2008, p. 505). However the question remains, is there a solution to the problem of time and the “other” assigned duties many reading coaches are experiencing that take them away from their critical role?

A possible solution to the problem would be introducing a data technology tool for coaches and teachers to utilize in making instructional decisions. Since a goal of Reading First is

to “encourage and support teachers’ efforts to use assessment data to help them individualize instruction” a data technology tool would be a resource to improve instruction (Roehrig et al., 2008, p. 378).

Florida Assessments for Instruction in Reading (FAIR)

The FAIR provide teachers with data that outlines a student’s literacy needs. FAIR are given to most struggling readers in the state of Florida and those most at risk for having reading problems. FAIR data are useful to all reading, content area teachers, and specialists or problem-solving teams, such as speech pathology specialists and RTI teams because FAIR provides curriculum and strategy recommendations specific to each student’s needs. For example, students who score into a certain FAIR reading profile (box 1) may benefit from being taught to use the recommended strategy SQ3R, a research-based strategy that can be employed in the content areas to increase reading comprehension (Huber, 2004). PMRN also provides teachers with a parent letter so that parents can be informed of student progress, which provides teachers with an opportunity to share with parents or caregivers ways to help their child be successful, as a partner with the teacher. So, for example, teachers could teach parents the SQ3R strategy so they can help reinforce their child learning and using the strategy when studying at home. Secondary content area teachers may especially benefit from using FAIR data because these teachers do not typically think it is their job to embed literacy strategies in their instructional practices (Sturtevant, 2003). FAIR data are connected to FAIR resources found on www.fcrr.org and Literacy Essentials and Reading Network (LEaRN) at <http://www.justreadflorida.com/learn/>. These sites provide teachers with instructional strategies and resources that explain how to use

research-based strategies and link them to video demonstrations to promote the literacy skills of students.

Florida reading coaches are the instructional leaders charged with helping teachers understand and utilize FAIR data . The state has identified reading coaches and district personnel as those who need to become master trainers for FAIR at school sites as indicated at <http://www.fldoe.org/faq/default.asp?Dept=4&ID=1330#Q1330>. Reading coaches in Florida use this system because it, “identifies students who are not performing as expected based on the performance of other children at the same grade level, identifies the skills they are struggling with, and makes suggestions for student grouping” (Roehrig et al., 2008, p. 265). Reading coaches in Florida have been given a role as data experts to help teachers positively affect student achievement in the classroom by strategically using FAIR data to create optimally designed instruction. In Florida, Statute 6A-6.053, K-12 Comprehensive Research-Based Reading Plan, indicates that part of a reading coaches’ job is to, on an on-going basis, provide professional development and training for all teachers in analyzing data and using data to differentiate student instruction.

The FAIR has been found to predict Florida Comprehensive Assessment Test (FCAT) scores in grades 3-12 (Foorman & Petscher, 2010; Florida Department of Education, 2005). The FCAT consists of a criterion-referenced test that is administered to students in grades 3-11 in all Florida Public Schools in order to measure the academic progress of students in subjects such as: reading, mathematics, science, and writing (“FCAT Briefing,” 2005). The FAIR has been evaluated by the Buros Center for Testing (Greenberg, 2010). The Buros Center is a credible,

independent evaluation center at the national level which has given credence to using the FAIR to assess students (Buros, 2010; Greenberg, 2010).

The Buros Center's (2010) report on FAIR stated that FAIR has the primary purpose of providing assessment that can be utilized to shape instruction. The Buros Center report further explained that the FAIR's primary purpose is to improve student reading skills. According to the Buros Center (2010), "for Grades 3-12, the FAIR was developed in response to the recognized need for formative assessment throughout the academic year, the results of which can be used to indentify instructional needs, monitor progress, and assist instructional efforts that will increase reading ability toward grade-level standards" (Buros, 2010, p. 39).

The FAIR for grades 3-12 indicates reliability of scores for the FCAT Success Probability Score (a predictor of FCAT), where "the coefficients across grades are very high," all around .90 (Buros, 2010, p. 43). The validity, using the negative predictive power, of the grades 3-12 also was high, at a median of .925 for all with the exception of grade 10 which only showed a negative predictive power of .54. Overall, in the summary offered by the Buros Center (2010) they noted "in general, psychometric evidence is relatively complete and supports the test's intended uses" (Buros, 2010, p. 55).

The FAIR therefore is a powerful vehicle in promoting student achievement and each reading coach has the responsibility of teaching teachers how to use the data generated by FAIR in classrooms to assist in providing differentiated instruction to students. Important to this study, the Florida Department of Education also includes in all of the FAIR trainings for the FAIR Master Trainer/reading coach a data technology tool to help teachers utilize FAIR data. The data

technology tool, found on the www.fcrr.org website, helps teachers quickly calculate student FAIR reading profiles, trend out data, and create small groups for differentiated instruction. The state-adopted tool was developed by the researcher and her husband. The state-adopted tool provides suggested curriculum and strategies specific to the needs of students based on the FAIR reading profiles. It is the expectation of the state, therefore that reading coaches teach teachers how to use this data technology tool to assist them in effectively utilizing data.

Data Technology Tools and Systems

Districts and schools that use the federal dollars associated with No Child Left Behind have a legal responsibility attached to receiving those dollars to report and track student achievement publically. In fact, more than a half billion federal dollars have been used by states in order to build longitudinal technology systems that contain student data in order to “support data-driven decision making” (“What Teacher,” 2012, p. 1; <http://dataqualitycampaign.org>). In Florida, the public has access to AYP reports, which categorize FCAT achievement data and graduation rate information by subgroups year to year on the School Accountability Report site of the Florida Department of Education (<http://schoolgrades.fldoe.org/>), therefore demonstrating whether NCLB requirements have been met or not. These reporting demands have led districts and schools to purchase data technology tools to assist in the required data tracking and reporting requirements of NCLB (Mandinach et al., 2006; Mesmer & Mesmer, 2008; Fuchs & Fuchs, 2006).

Although NCLB in 2001 spurred the growth of data technology tools or systems being utilized nationally by districts and schools, the data technology and data were not usually accessible to teachers to use for classroom instruction (Miller, 2009; Wayman & Cho, 2009).

Historically, teachers are not likely to receive data that can help them improve student achievement in the classroom, despite states and districts collecting data and housing it in data bases (Miller, 2009 & Wayman, 2005). Wayman and Cho (2009) explained that states and districts have been using data tools and systems to comply with mandates in reporting student data and only more recently have data tools and systems been shared with teachers for the purpose of improving the instruction that students receive.

In 2005, Wayman argued that it is crucial for districts and schools to go beyond the requirements of using data in the ways set forth by NCLB and provide student data to teachers. Wayman (2005) found that student data are often stored in ways that make it hard for teachers to obtain, manipulate, and understand. Wayman (2005) states, “although schools have been “data rich” for years, they were also “information poor” because vast amounts of available data they had were often stored in ways that were inaccessible to most practitioners” (Wayman, 2005, p. 296).

The U.S. Department of Education’s *National Educational Technology Trend Study* found that data systems are being used by schools in attempts to improve schools; however, the data have had minimal impact on teacher’s day-to-day instructional decisions (Bakia et al., 2008). The study further found that it is uncommon for district and state data systems to be fused together with classroom data (Bakia et al., 2008).

Research clearly highlights that teachers need assistance in utilizing technology tools. Wayman, Cho, and Johnston (2007) found in their research that it is typical that teachers are not assisted with effectively utilizing data into their workdays. Research indicates that teachers

“lack the data analysis skills necessary to use data to make sound instructional decisions” (Nelsestuen et al., 2009, p. 12). The need for teachers receiving data in usable ways is important as it has become an expectation that teachers use data to shape instruction. Technology can be an ally for teachers in this endeavor, as Arne Duncan stated at the American Enterprise Institute in 2010, “Technology can play a huge role in increasing educational productivity” (Greaves et al., 2010, p. vi). To assist in this mammoth endeavor, the Data Quality Campaign was formed by interested stakeholders, including the Bill & Melinda Gates Foundation, AT&T, and others. The Data Quality Campaign is a “national collaborative effort” to provide resources and assistance for states in implementing effective data systems that can track student data longitudinally for the purpose of increasing student achievement (<http://dataqualitycampaign.org/about>, para. 1). Additionally, they focus on improving the data literacy skills of educators (“What Teacher,” 2012). Still, research is indicating that most of data that teachers have access to in technology tools or systems are most likely to be access to student grades and attendance, and not data that teachers need to make for making data-based decision making to help student perform optimally (Gallagher et al., 2008; Means et al., 2009; Miller, 2009).

One data system that has shown promise is New York’s Grow Network, which can be used by educators to provide student data and pinpoint exactly what a student is having difficulty mastering, in relation to skills and standards, and then provides links to instructional resources a teacher can use to impact student achievement. The resources include suggested teaching strategies and activities to help teachers teach students in ways that will improve their standards-based learning. The Grow Network data system helps teachers differentiate student data by providing different levels of data focus (Brunner et al., 2005). Other similar technology systems

and tools that may vary slightly from the Grow Network are being utilized in states such as Alaska, Arizona, Indiana, and Texas (Pinkus, 2009; Brunner et al., 2005).

Technology data tools may be a solution to assist teachers who lack data literacy skills, such as comprehending data, interpreting data, finding trends in data, and using data efficiently (Means et al., 2009; Miller, 2009; Wayman, 2005). The research is pointing to a need for data technology tools to help teachers perform optimally. Vygotsky's sociocultural theory of learning supports the use of tools to grow knowledge. According to Vygotsky's theory, people use tools (mental tools or physical tools) to take in information and mediate it into meaning and action (Gee, 2000).

Technology Acceptance Model (TAM)

The TAM has been used to determine how external factors affect or influence teacher's use of technology. The TAM was designed to predict "computer usage behavior" (Teo, Lee, Chai, & Wong, 2009, p. 1). The TAM model has been shown to be empirically successful when predicting if a user will use a technology according to the authors of *Understanding pre-service teachers' computer attitudes: Applying and extending the Technology Acceptance Model (TAM)*. In fact, according to the authors, TAM has two particular variables that predict an individual's probability of using a technology; perceived ease of use and perceived usefulness (Teo, Lee, & Chai, 2007).

In *Understanding pre-service teachers' computer attitudes: Applying and extending the Technology Acceptance Model (TAM)* the authors reveal that perceived ease of use and perceived usefulness determined pre-service teachers' attitudes towards computer use (Teo et al., 2007). External factors that affect the perceived ease of use and perceived usefulness include attitudes,

beliefs, and experiences (Pynoo et al., 2011). Additionally, computer self-efficacy is a factor that impacts perceived ease of use (Venkatesh, 2000).

Computer self-efficacy is a person's belief that they have the abilities to successfully use a technology (Compeau, Higgins, & Huff, 1999). The concept of self-efficacy stems from the work of Bandura (Compeau et al., 1999; Bandura, Adams, & Bayer, 1977). Bandura, Adams, and Bayer (1977) found that "perceived self-efficacy influences level of performance by enhancing intensity and persistence of effort" in completing a task (P 125). Furthermore, Bandura et al. (1977) found that behavioral change is dependent on cognitive mechanisms, such as perceived self-efficacy. Research by Compeau, Higgins, and Huff (1999) found a relationship between computer self-efficacy and computer use, which showed that the higher a person's computer self-efficacy the more likely they were to use a computer. Hu, Clark, and Ma (2003) found that perceived computer self-efficacy does directly affect the behavioral intentions an individual has to use or accept a technology. Thus, computer self-efficacy may play a major role in determining how much effort and perseverance individuals may apply in using a data technology tool. Furthermore, finding ways to improve computer self-efficacy may be crucial in the technology acceptance one has towards utilizing a data technology tool.

Teo, Lee, and Chai, (2008) found in their study that pre-service teacher attitudes predicted computer usage. Subjective norms also predicted pre-service teacher computer usage (Teo et al., 2007). An example of a subjective norm would be administrative support in using a technology tool. This is important as the research indicates that trainings, relevant materials, and support from administrators influence the use of computer technologies (Pynoo et al., 2011).

Hu et al. (2003) believe that many public school teachers world-wide are resistant to technology. Their research indicates that perceived ease of use and perceived usefulness are factors that heavily influence whether or not teachers will use technology. One influence, job relevance, was regarded as a large factor in predicting perceived usefulness (Teo, Lee, & Chai, 2008). As an indication of the lack of agreement on teacher usage of technology, a teacher survey study by the Bakia et al. (2008), found that most teachers possess positive outlooks regarding receiving support in utilizing data from data technology systems.

Smarkola (2007) argued that student teachers and experienced teachers will favor using the internet over technology tools that are designed to specifically impact their instructional practices. This research presented by Smarkola (2007) found that, in agreement with the *National Educational Technology Trends Study* (2009) survey, teachers needed support from resources, administrators, and computer-integrated hands-on practice in order for them as a collective group to be more open to technology tools. She believes, as Davis (1989) the inventor of the TAM model, that “an individual’s technology acceptance is a crucial factor in determining the success or failure of a computer systems project” (Smarkola, 2008, p. 1197). It is apparent that variables, such as perceived usefulness, perceived ease of use, computer self-efficacy, and subjective norms affect whether or not educators will use a technology tool or application.

Summary

The literature review has revealed that reading coaches need to spend more time helping teachers analyze and use student data to create optimal instruction and that technology data tools may be able to assist in this endeavor. These findings have helped fuel the study. Since research has not provided insight about the technology acceptance level reading coaches have in using

technology data tools with teachers, it is important to learn how data technology tools may be received and used by reading coaches to improve their job performance and assist teachers in providing timely instructional assistance.

Furthermore, it is imperative to learn what schools, districts, and states can do to support reading coaches and teachers in helping them use technology tools or systems to impact student achievement. The research has revealed that teachers may benefit from utilizing data tools; however the research also revealed that educators may need support, guidance, and trainings in using data tools in order for them to be successful in impacting student achievement. Overall, there are insufficient research data on reading coaches using data technology tools with teachers. The primary purpose of this study is to add to this research base by investigating the behavioral intentions reading coaches have in using a data technology tool with teachers.

CHAPTER THREE: METHODOLOGY

The purpose of this chapter is to report all phases of the methodology utilized in the study. It is divided into the following five sections describing: 1) research design, 2) sampling method, 3) instrumentation, 4) method of data analysis, and 5) assumptions and delimitations of the study.

Research Design

The district-adopted Teacher Data Tool, developed by the researcher and her husband, was created for the purpose of providing all teachers of grade three through twelve students with assistance in utilizing Florida Assessments for Instruction in Reading (FAIR) data for the benefit of promoting student literacy skills and achievement. Reading coaches who participated in this study completed the Behavioral Intentions Survey (BI Survey in Appendix B) to determine their behavioral intentions towards using the Teacher Data Tool with teachers. Furthermore, the BI Survey design was designed to help determine what variables (perceived ease of use, perceived usefulness, computer self-efficacy, and subjective norms), may influence behavioral intentions and whether there is a difference in the behavioral intentions of coaches at various school levels (elementary, middle, or high). According to Davis (1989) and Venkatesh and Davis (2000), behavioral intentions predict system use. The model in Figure 1 shows the adaptation of the Technology Acceptance Model (TAM) that will guide the study.

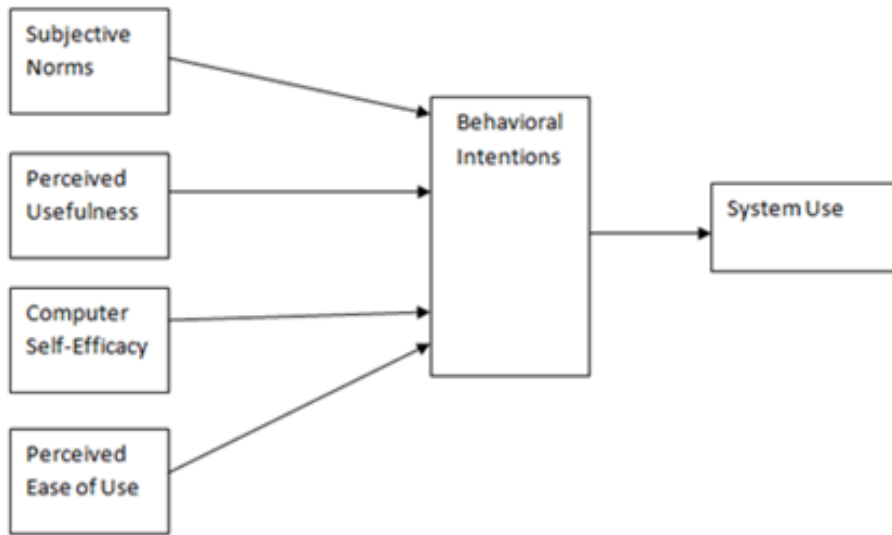


Figure 1: Adaptation of the Technology Acceptance Model (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh, 2000)

The Teacher Data Tool is primarily driven by FAIR data, but also student AYP data, and data teachers collect can be entered into the tool. Some of the functions of the Teacher Data Tool include: immediately calculating student FAIR reading profiles and recommended further assessments; an interactive graph that can track student oral reading fluency over time; a place to document actions, such as instructional settings and strategies utilized; a progress monitoring feature that can track student progress and teacher actions throughout the school year; and ways to manipulate and trend out data for differentiated instruction purposes.

The main focus of this research is to study how reading coaches assist teachers in utilizing data technology tools, such as the Teacher Data Tool. Reading coaches are hired to optimize the effectiveness of teachers (Sturtevant, 2003). Reading coaches are expected to show teachers how data technology tools can be utilized to understand, analyze, and use student data.

Improvement in the use of technology by classroom teachers is vital to improving student achievement (Wayman, 2005).

This study attempted, in part, to discover reading coaches' behavioral intentions toward utilizing a data technology tool with teachers in an effort to help teachers understand and use student data to drive instruction. Reading coaches are critical players in helping teachers use data tools to drive classroom instruction. If reading coaches did not have behavioral intentions toward using a technology tool to assist teachers in utilizing data, then teachers may not be receiving the kind of help and resources they may need in making data-based decisions to improve instruction in a quicker and more efficient manner.

Further value in this study has been in determining what variables may affect reading coaches' behavioral intentions to use a tool. For example, if the variable computer self-efficacy affected coaches using the tool with teachers then it may be possible to find ways to improve their perceptions of their own computer self-efficacy skills in the hopes of increasing their behavioral intentions.

The Teacher Data Tool relies mostly on the data provided by the FAIR. The FAIR provides educators with a large quantity of data that helps determine appropriate instruction. FAIR assessments are given to nearly all struggling readers in the state of Florida and those most at risk for having reading problems. Data produced through FAIR are applicable in many content areas including science, math, social studies, and reading.

The FAIR made its debut in Florida public schools in August of 2009 for students in grades K-12. The assessment was created by the collaborative efforts of Just Read, Florida! and the Florida Center for Reading Research ("Florida Assessments," 2009). The FAIR provides

educators with screening, diagnostic and progress monitoring data that are intended to help educators shape the instruction students receive (“Florida Assessments,” 2009). The screening data provided by FAIR helps educators identify students that are reading below grade level. The diagnostic data that FAIR provides is helpful to educators because it reports the specific reading needs a student possesses. Progress monitoring data provided by the FAIR enables educators to determine if instruction and intervention is working which is accomplished by the formative data FAIR reports during the three times a year it is administered to students (“Florida Assessments,” 2009).

For students in 3-12 grades, the main FAIR assessments include the Reading Comprehension/Broad Screen, Maze, and Word Analysis which are assessed on a computer (“Florida Assessments,” 2009). During the computer-adaptive Broad Screen assessment students answer questions for one to three passages (“Florida Assessments,” 2009). The Broad Screen yields many scores for students including, but not limited to, an FSP (FCAT Success Probability) score, a reading comprehension score, and a breakdown of how the student is predicted to score on each area assessed by the reading FCAT, including the following clusters: vocabulary, reading application, literary analysis for both fiction and nonfiction, and informational text/research process (“Florida Assessments,” 2009). The FSP score predicts the likelihood a student will obtain a 3 or above score on the reading FCAT; anything less than a score of 3 indicates the student is reading below grade level. The reading comprehension score indicates the current reading comprehension abilities a student possesses (“Florida Assessments,” 2009). FCAT cluster scores provide information indicated by a “low” “medium” “high” or “NA” score that indicates the level of mastery for each cluster (“Florida Assessments,” 2009). “NA” scores

are reported if there are a lack of questions that could generate a score for a student (“Florida Assessments,” 2009).

If a student scores into a range indicating there is a reading deficit within the Broad Screen then the student takes the Targeted Diagnostic Inventory which is comprised of the Maze and Word Analysis inventories (“Florida Assessments,” 2009). During the Maze assessment students read two grade-level passages that are timed. Three minutes are allotted for students to enter answer selections for each passage during the Maze (“Florida Assessments,” 2009). During the Maze assessment students read a text and while reading encounter places embedded within the text that require the student to select a word, from a word bank, that makes the most sense in the text as they read (“Florida Assessments,” 2009). There is a 1 to 7 ratio of Maze items per words in each passage (“Florida Assessments,” 2009). The Maze assessment provides information about a student’s silent fluency and low level comprehension abilities (“Florida Assessments,” 2009). Fluency is a determinant that can impact reading comprehension (“National Reading,” 2000). The percentile rank is one score generated by the Maze, which provides educators with a score that compares a student to other students of the same grade level who took the assessment in Florida (“Florida Assessments,” 2009).

Finally, the Word Analysis assesses the student’s spelling abilities, as spelling is correlated to reading abilities (Foorman & Petscher, 2010). The computer-adaptive Word Analysis part of the assessment requires students to listen to words and spell them (“Florida Assessments,” 2009). A few scores are yielded from the Word Analysis, one being a percentile rank score that reports how the student scored compared to other students in Florida in the same

grade level (“Florida Assessments,” 2009). The Word Analysis is helpful in determining a student’s orthographic, morphological, and phonological word knowledge. The words students are required to spell for the Word Analysis assessment are given in isolation of any text (“Florida Assessments,” 2009).

According to http://www.fcrr.org/FAIR/3-12_Decision_Tree.pdf three scores, the Reading Comprehension, Maze, and Word Analysis are used to create FAIR reading profiles that each student will score into when taking the FAIR. FAIR reading profiles are useful to educators because they provide curriculum recommendations and strategy suggestions that can be used in any reading and content area class. Students can also receive differentiated instruction and have their progress monitored over the three assessment periods of FAIR using the FAIR reading profiles. Some benefits of the Teacher Data Tool are that it will automatically calculate student FAIR reading profiles once scores are entered into the tool, organize the data for differentiation purposes, and monitor how students progress according to FAIR reading profile scores for each of the three assessment periods. Thus, the Teacher Data Tool helps teachers quickly determine student needs and provides guidance to teachers as to what curriculum and strategies may be beneficial to each student in order to promote learning.

Other components of the FAIR that may be administered between the three FAIR assessment windows and do not occur on the computer are the Ongoing Progress Monitoring option and the Informal Diagnostic/Progress Assessment for Grades 3-12 Tool Kit (“Florida Assessments,” 2009). The Ongoing Progress Monitoring option allows educators to evaluate oral reading fluency every three to four weeks by using provided Oral Reading Fluency probes

(“Florida Assessments,” 2009; “Use of,” n.d.). The Teacher Data Tool provides teachers with a graph where they can record and track student fluency scores over time. The Informal Diagnostic/Progress Assessment for Grades 3-12 Tool Kit provides teachers with further assessments (if FAIR computer scores indicated a need for further assessment to pinpoint reading needs), such as a Phonics Assessment and also provides passages and templates for helping students practice using reading strategies, such as Question-Answer Relationships (QAR) (“Florida Assessments,” 2009). The Teacher Data Tool was created for the purpose of providing all teachers, not just reading teachers, with assistance in utilizing FAIR data for the benefit of promoting student achievement. It is important to note that content area teachers in secondary schools typically do not have the kind of data to help them improve their students’ literacy skills and achievement in their respective areas (Gallagher et al., 2008; Means et al., 2009; Miller, 2009). Therefore, the Teacher Data Tool provides all teachers, and those who typically do not have access to the kinds of student data that is helpful for instructional purposes, with the following specific functions:

- provides ways to assist educators in determining student FAIR reading profiles in a quick and effective manner and provide an option to group students with like needs
- indicates which students need to take further assessments from the Informal Diagnostic/Progress Assessment for Grades 3-12 Tool Kit and provides a place to document results and correlating resources to help improve student literacy skills
- supplies resources (strategy explanations and examples, short videos demonstrations of strategies, etc.) that can be used to teach students, based on their needs according to data

- provides a progress monitoring options
- supplies an action log for teachers connected to the FAIR that allows teachers to input four actions: instructional settings, strategies used, professional development, and coach involvement with a fifth column available to enter notes about a specific student
- offers an interactive graph that can graph student oral reading fluency with technology
- provides filter functions that allow for teachers to organize data, manipulate data in different ways, and identify trends in data (for example, five students who are in the same FAIR reading profile can be quickly determined and used to create a small group)

When taking into consideration what teachers need a technology tool to do, research suggests that teachers need a flexible technology tool like the Teacher Data Tool that is designed to help them understand data, organize data, analyze data, and provide them with quick links to readily available resources aligned to state standards, curriculum, and strategies that will propel student achievement further (Gee, 2000; Brunner et al., 2005).

Research emphasizes that there is much importance in understanding a learner's background and needs when designing for a learner (Telg et al., 2005). When creating a tool for users it is important to consider the user. The Cognitive Load Theory was utilized when devising the Teacher Data Tool. The Cognitive Load Theory can aid a designer in the process of design by providing a theoretical framework for understanding a learner's cognitive intake abilities (Cook, 2006).

The Cognitive Load Theory emphasizes the importance of understanding the cognitive structures of a learner's brain, including the working memory and long-term memory. The theory explains that the working memory of an individual is limited, while the long-term memory is unlimited; however, they interact with each other to form meaning. This is because the long-term memory is used by the brain to retrieve information (prior knowledge) that helps make meaning out of what is presented in the working memory (Cook, 2006).

The Cognitive Load Theory further explains that the working memory can be bogged down by too much information at one time and rendered less effective and less able to transfer information to the long-term memory banks (Cook, 2006). However, Kirschner (2002) explains that using more than one way of presenting the same data to the working memory expands the capacity of the working memory and thus its likelihood of transferring information to the long-term memory. This process is referred to as *multiple representations* (Kirschner, 2002).

By using prior knowledge and tapping into the long-term memory, to assist the working memory in understanding a concept, and by using multiple representations of concepts, the Teacher Data Tool is aimed to be more useful and memorable to teachers. To accomplish this task, the Teacher Data Tool has a component that is identical to a data tool adopted by the Florida Department of Education, which is featured on their fcrr.org website as well as in all FAIR trainings for teachers, reading coaches, and administrators. The Florida Department of Education encourages educators to use the state-adopted tool when calculating student reading profiles and organizing them for differentiation purposes.

When considering how the brain processes information in the framework of the Cognitive Load Theory, one does not want to overload the user with too many options. In order to avoid

cognitive overload, there are ways of simplifying the data so that the user can select what data to view in organized ways (Ludwig, Pritchard, & Walker, 2009). This sustainable design principle embodied the 80/20 rule of design (Lidwell, Holden, & Butler, 2010). The 80/20 rule of design helps a user focus on the important elements of a tool instead of overloading a user with too much information at once and is featured in the Teacher Data Tool when filters are used to allow an educator to view just the information they want to see, such as only those students who scored into the FAIR reading profile of 2+4 or the FAIR reading profiles of those who are in a specific AYP subgroup. (Lidwell et al., 2010).

Another sustainable design outlined by Ludwig, Pritchard, and Walker (2009) is implanting into design a control when the creator does not want the user to change a part. This design principle is called the constraint principle (Lidwell et al., 2010) and is evident in the Teacher Data Tool when drop boxes limit the input choices a user can enter into a data field to ensure that only the language desired is used to for descriptive data purposes. A similar, but more flexible example of design control is also utilized in the Teacher Data Tool, and it is referred to as the forgiveness principle of design (Lidwell et al., 2010). The forgiveness principle is apparent in the Teacher Data Tool when areas that identify a student are grayed out so that when a user inputs data on a new page the user will know immediately to assign data to a corresponding student identified row.

Important to a learner are the visual aesthetics present in a design that enable the learner to understand presented information in a more effective manner (Parrish, 2007). According to Dewey (1934/1989), aesthetic experiences are meaningful and create immersion. So, color has

been used in design of the tool to increase the aesthetics of the tool in order to highlight meaningful information for classifying or viewing.

Importantly, effective design has a focal point or underlying theme (Frey & Pumpian, 2006; Parrish, 2007). The focal point or theme of the Teacher Data Tool is to give educators a data tool that they can use to positively impact student achievement. The tool is a cause and effect instrument designed to promote teacher action based on student data and their own teacher actions throughout the school year as documented after each assessment period. The tool allows teachers to reflect if current practices are working and impacting student success positively or if they need to change their actions (such as increase small group time or introduce a new way of learning material through a different strategy) to move students into a path of success.

The goals of the Teacher Data Tool are to help teachers actively use FAIR data to shape instruction in a flexible manner that is intended to positively impact student success and promote reflective, action-oriented teaching. Another goal is to save teacher the time it may otherwise take in best utilizing student data. Time is a commodity in short demand that teachers need most to plan, prepare, and implement quality instruction (Means et al., 2009).

Imperatively and according to research by Miller (2009), teachers need help reading interpreting their data and clearly seeing patterns, and the Teacher Data Tool is designed to assist teachers in this need by helping teachers identify patterns in data, such as students who may be grouped by like needs (Means et al., 2009).

Finally, the design of the Teacher Data Tool enables teachers to do what the federal government, state, district, and all stakeholders are expecting them to do: create instruction that is specific to student needs according to data.

The design of the BI Survey enabled stakeholders to learn how reading coaches' behavioral intentions may impact teacher development in utilizing a data technology tool that is designed to aid teachers in creating relevant and impactful instruction to students based on their needs. Furthermore, the design of the BI Survey helped identify what variables play a role in determining reading coaches' behavioral intentions to use a technology data tool with teachers. Finally, the design of the BI Survey provided insight into what reading coaches felt are important for the researcher to know about when using technology data tools with teachers. Since the Teacher Data Tool is providing the very kind of assistance that is being recommended by research to help teachers devise strategic and impactful instruction, the results of this study, enabled by the BI Survey, are relevant to the field of education.

Sampling Method

The unit of sampling in this study was the reading coach. The survey was sent to all reading coaches in a large urban school district in Florida. A census of the population of the estimated 163 reading coaches was taken. The 2011-2012 K-12 Comprehensive Research Based Reading Plan for the district reading coaches examined in this study does not provide information as to how many reading coaches were from high school, middle school, or elementary school levels, although it is assumed that because there are a much greater amount of elementary schools in the district that the population of elementary reading coaches represented in the 163 estimation of reading coaches is the highest represented group. All reading coaches of

various ages, backgrounds, and experiences were invited to take the survey. The responses were classified as elementary, middle, and high school reading coaches depending on their indication of school level mostly served.

61 reading coaches or 37% of the estimated population of reading coaches responses were included in this study, even though 69 responded. Responses were not included if a reading coach indicated that they had not viewed the tool prior to the survey, if the individual answered “I don’t know” in response to questions, and if a coach did not answer many questions. Of the 61 individuals included in the study, 32 of them were elementary school reading coaches, 16 were middle school reading coaches, and 13 were high school reading coaches.

After receiving permission to conduct the study from the University’s IRB found in Appendix A and the district’s research department, an email was sent to two of the district’s administrators who oversee the district’s reading coaches. Then the two district administrators sent out the survey with an invitation to take it via an e-mail to the entire reading coach population in the county. The data was collected using Survey Monkey. In the email, the participants read through a consent form to participate waiver prior to taking the survey. The survey was deployed over a two-week time period after Thanksgiving. All reading coaches received a reminder email after one week from the initial email to let them know they still had time to participate if they were interested in being a part of the study.

Instrumentation

The BI Survey was created to determine coaches’ perceptions of behaviorable variables including perceived usefulness, perceived ease of use, computer self-efficacy, subjective norms, and behavioral intentions. It is estimated that the survey took five minutes of time to complete.

The quantitative instruments and corresponding item stems aimed at predicting reading coaches' behavioral intentions towards using the Teacher Data Tool in an effort to determine what factors will predict the use of this technology. Survey Monkey was selected because of its ability to track answers, transfer data into SPSS, and due to the ease of nature in using links that are easily inserted into emails. SPSS was utilized to generate the statistics presented in this section and to help answer the research questions. There was only one qualitative question that was analyzed by the researcher in a coding method.

The BI Survey (Appendix B) was utilized to determine reading coaches' perceptions of behavioral variables including perceived ease of use, perceived usefulness, computer self-efficacy, subjective norms, and behavioral intentions. The quantitative survey questions were designed using instruments and item stems by Davis (1989), Venkatesh and Davis (2000), and Venkatesh (2000). In the survey, five instruments are represented, including perceived usefulness, perceived ease of use, computer self-efficacy, subjective norms and behavioral intentions. The item stems that are used to quantify each of the instruments range from two to six items. Each item stem used language directly from Davis (1989), Venkatesh and Davis (2000), and Venkatesh (2000) or in, some cases their language was modified slightly to fit the data tool being studied. Content validity and construct validity were established with the item stems used to construct the BI Survey based on the research of Davis (1989), Venkatesh and Davis (2000), and Venkatesh (2000).

The BI Survey was piloted with secondary reading coaches in March, 2011 in a large urban school district in Florida. The dependent variables in the survey yielded strong reliability indicators according to Cronbach's Alpha, ranging from .752 to .956. A score of more than .70

indicates a reasonable relationship or measure amongst variables for Cronbach's Alpha (Nunnally & Bernstein, 1994).

As mentioned, the BI item stems were either not altered or modified slightly to fit the tool being evaluated. For example, one of the behavioral intention item stems in the BI Survey states, "I predict I will use this tool in the future," and in an article by Venkatesh (2000) he used the behavioral intention item stem, "Given that I have access to the system, I predict I would use it" (Venkatesh, 2000, p. 360). Another example from the BI Survey for an item stem in the perceived usefulness states, "Using the Teacher Data Tool saves time in planning for student instruction," while in the Davis (1989) article, the item stem that inspired the BI Survey item stem for perceived usefulness was, "Using electronic mail saves me time" (Davis, 1989, p. 324). Finally, an example from the Venkatesh and Davis (2000) article would be the use of their item stem for perceived ease of use, "I find it easy to get the system to do what I want it to do," which inspired the BI Survey item stem for perceived ease of use, "I find it easy to get the tool to do what I want it to do" (Venkatesh & Davis, 2000, p. 201). Permission to use the item stems in the BI Survey was gained from both authors through emails (found in Appendices D and E). Additionally, the BI Survey collected demographic information; including years as an educator, reading background, years in current role, and assigned school level(s). These independent variables were used to learn about possible correlations with the dependent variable "behavioral intentions" and to share information about those individuals being studied.

Finally, one qualitative question was asked in the survey to determine and trend out any like thoughts reading coaches shared regarding using data tools in helping teachers. This question was analyzed by the researcher in a coding method where data trending was applied for

like responses. The terms that were identical or phrases that conveyed a similar meaning were coded together and frequent terms use was used to form a title for a trend, such as “user-friendly.” Since surveys are quantitative by nature, the qualitative question enabled the researcher to gain information about reading coaches’ thoughts on using a data technology tool.

Method of Data Analysis

A reliability analysis was utilized to determine internal consistency of dependent variables using Cronbach’s Alpha for all coaches combined. The survey mean and median values of the dependent variables (using the Likert scale) as they stand alone were examined. The Likert Scale scores were: 1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree.

When analyzing dependent variables using Cronbach’s Alpha for reliability measures, the process was done with two data sets (Tests 1 and 2) and all results from both data sets yielded higher than .70 for Cronbach’s Alpha for all reading coaches combined. The first data set generated the highest Cronbach’s Alpha scores and the second data set yielded the second highest Cronbach’s Alpha scores for all reading coaches combined. The researcher removed item stems within an instrument in some cases to yield the highest Cronbach’s Alpha scores and used the same item stems when analyzing every group including all reading coaches, elementary school reading coaches, middle school reading coaches, and high school reading coaches. No item stems were removed from behavioral intentions, which only had two item stems that yielded over .90 for reliability. To show the item stems that were included in each of the data sets, please see Appendix C. The reliability analysis is noted in Table 1.

Pearson's correlation was used when examining the relationships between the dependent variables to behavioral intentions (also a dependent variable), as well as independent variables to behavioral intentions. The further the Pearson's correlation from zero, either positive or negative, the stronger the relationship between variables (Vaughan, 2001). P values were also used and assisted in determining whether to "reject" or "fail to reject" the null hypothesis for each pair correlated. Rejecting a null hypothesis indicates that there is a relationship between variables and failure to reject a null hypothesis indicates that there is not a relationship between variables. The r scores provided information regarding the degree to which one variable impacted another, which was denoted by an asterisk(s) when a significant relationship was generated. The R-Squared scores allowed for percentages to be generated, allowing for predictions to occur for how much each variable influenced behavioral intentions.

Assumptions and Delimitations

The following lists include assumptions and delimitations of this study.

Assumptions

1. Behavioral variables play a role in reading coaches' behavioral intentions in using a data technology tool with teachers.
2. The Teacher Data Tool is a valid and reliable instrument.
3. The reading coaches' ratings on the Teacher Data Tool are reliable.

Delimitations

1. This study is not seeking explanations for behavioral intentions on the part of reading coaches.
2. This study looks at behavioral intentions of reading coaches in only one school system.

CHAPTER FOUR: FINDINGS

The purpose of this chapter is to report the data collected in this research. A summary of the analysis of procedures and related information is presented herein.

Description of Data Collection

The data was collected using the Survey Monkey system within a two-week time period after Thanksgiving. The data was then uploaded into SPSS. The instruments within Survey Monkey are available in Appendix C. All responses received from participants were collected through the Survey Monkey system.

Reliability Analysis

Cronbach's Alpha was utilized to determine the reliability of the dependent variables used in the study. A reasonable relationship is indicated by a score greater than .70 (Nunnally & Bernstein, 1994). Table 1 represents the reliability indicators for Test 1 and Test 2.

Table 1
Cronbach's Alpha for Test 1 and Test 2

Dependent Variable	Test 1	Test 2
Perceived Usefulness	.871	.867
Perceived Ease of Use	.906	.901
Computer Self-Efficacy	.803	.790
Subjective Norms	.892	.832
Behavioral Intentions	.944	.944

Research Question One

Research question one: What behavioral intentions do reading coaches have when utilizing a data technology tool with classroom teachers? Descriptive statistics were generated.

The traditional Likert Scale was used for data analysis in this study. The Likert Scale scores were: 1.0=strongly disagree, 2.0=disagree, 3.0=neutral, 4.0=agree, 5.0=strongly agree, and "I don't know". All "I don't know" responses were excluded in the data analysis. Also, one individual did not answer the majority of questions and their data was also excluded. Scores that were over 3.0 indicated stronger agreement for variables.

In analyzing the behavioral variable mean scores, reading coaches in each group (elementary school coaches, middle school reading coaches, and high school reading coaches), collectively agreed that they have behavioral intentions toward using the data technology tool with teachers as noted by scores over 3.0. Elementary coaches showed a high likelihood of using the technology data tool because their mean was over 4.0. All of this data, configured using mean scores and standard deviation scores are represented in Tables 2 ,3, 4, and 5. The medians

for all groups were four, which is a high indicator for their behavioral intentions to use the data technology tool. The medians are represented in Tables 2-5.

Overall, the hypothesis that: Reading coaches have specific behavioral intentions when utilizing a data technology tool with classroom teachers, is indicated to be correct when examining their high median and mean scores.

Table 2

All Reading Coaches: Descriptive Statistics

Behavioral Variable	n	Mean	Median	SD
Behavioral Intentions	61	3.8770	4	.99438

Table 3

Elementary School Reading Coaches: Descriptive Statistics

Behavioral Variable	n	Mean	Median	SD
Behavioral Intentions	32	4.1406	4	.89112

Table 4

Middle School Reading Coaches: Descriptive Statistics

Behavioral Variable	n	Mean	Median	SD
Behavioral Intentions	16	3.6250	4	.80623

Table 5

High School Reading Coaches: Descriptive Statistics

Behavioral Variable	n	Mean	Median	SD
Behavioral Intentions	13	3.5385	4	1.28228

Research Question Two

Research question two: To what extent do reading coaches utilize a data technology tool with classroom teachers based on different behavioral variables? To answer the question, Pearson's correlations were run for Test 1 and Test 2 data.

Guidance was used from Cohen and Manion (1994) to analyze Pearson's correlations and is illustrated in Table 6. The farther the Pearson's correlation from zero, either positive or negative, the stronger the relationship between variables (Vaughnan, 2001).

Table 6

Interpretation Guide for Rating the Correlations

Correlation Range	Interpretation
Less than 0.10	No Correlation (NC)
0.10-0.29	Small (S)
0.30-0.49	Medium (M)
0.50+	Large (L)

Test 1 data indicates that there are large, positive significant correlations for perceived usefulness and computer self-efficacy which impacts the behavioral intentions all reading

coaches have towards using a data technology tool. Furthermore, there is a medium, positive significant correlation between perceived ease of use impacting the behavioral intentions all reading coaches have towards using a data technology tool. The null hypothesis that perceived usefulness, perceived ease of use, and computer self-efficacy do not affect behavioral intentions is rejected in each case. The p value indicated that subjective norms do not affect behavioral intentions because there was a failure to reject the null hypothesis. All reading coach data represented are in Tables 7 and 8 for both Test 1 and Test 2

For Test 2 the data also showed strong, positive correlations that perceived usefulness, perceived ease of use, and computer self-efficacy all affect reading coaches' behavioral intentions to use a data technology tool. So, once again for perceived usefulness, perceived ease of use, and computer self-efficacy the null hypothesis was rejected. The second data set also showed that subjective norms do not affect the behavioral intentions all reading coaches have toward using a data technology tool as indicated by the failure to reject the null hypothesis.

In examining both Tests 1 and 2 it seems as though perceived usefulness is the greatest variable in determining if all reading coaches will use a data technology tool with teachers as both Tests 1 and 2 yielded large significant correlations.

Both tests provided R-Squared scores that indicate perceived usefulness, perceived ease of use, and computer self-efficacy highly predict whether reading coaches will have behavioral intentions toward using a data technology tool. Together these variables have a significant impact on the behavioral intentions of all reading coaches.

Table 7

Test 1: All Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	61	.542** (L)	29%	.000	Reject
Perceived Ease of Use	61	.390** (M)	15%	.002	Reject
Computer Self-Efficacy	61	.567** (L)	32%	.000	Reject
Subjective Norms	61	.217 (S)	5%	.093	Fail to Reject

**Correlation is significant at the 0.01 level (2-tailed).

Table 8

Test 2: All Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	61	.600** (L)	36%	.000	Reject
Perceived Ease of Use	61	.386** (M)	15%	.002	Reject
Computer Self-Efficacy	61	.477** (M)	23%	.000	Reject
Subjective Norms	61	.171 (S)	3%	.188	Fail to Reject

**Correlation is significant at the 0.01 level (2-tailed).

For elementary school coaches, every variable, including perceived usefulness, perceived ease of use, computer self-efficacy, and subjective norms all significantly, positively affected reading coaches' behavioral intentions towards using a data technology tool for both Tests 1 and 2. Large influences on the elementary reading coaches' behavioral intentions were perceived ease of use and computer self-efficacy for both Tests 1 and 2. Computer self-efficacy was the most likely to positively affect the behavioral intentions reading coaches have towards using a data technology tool in Test 1. For each variable tested the null hypothesis was rejected, indicating that each variable influences elementary reading coaches' behavioral intentions to utilize a data technology tool.

In both Test 1 and Test 2 the largest significant correlations were between perceived usefulness and behavioral intentions and between computer self-efficacy and behavioral

intentions. Both of these areas generated stronger statistical relationships than either perceived usefulness or subjective norms to behavioral intentions.

Using the R-Squared scores, one can predict how each variable will impact behavioral intentions. This is important because each one of these variables impact behavioral intentions separately, but in combination they have a large and important impact on the behavioral intentions elementary reading coaches have toward using data technology tools. The elementary school reading coach data are represented in Tables 9 and 10.

Table 9

Test 1: Elementary School Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	32	.470** (M)	22%	.007	Reject
Perceived Ease of Use	32	.565** (L)	32%	.001	Reject
Computer Self-Efficacy	32	.660** (L)	44%	.000	Reject
Subjective Norms	32	.566** (L)	32%	.001	Reject

**Correlation is significant at the 0.01 level (2-tailed).

Table 10

Test 2: Elementary School Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	32	.510** (L)	26%	.003	Reject
Perceived Ease of Use	32	.572** (L)	33%	.001	Reject
Computer Self-Efficacy	32	.552** (L)	30%	.001	Reject
Subjective Norms	32	.486** (M)	24%	.005	Reject

**Correlation is significant at the 0.01 level (2-tailed).

For middle school reading coaches, Test 1 and Test 2 generated significant, large positive correlations for perceived usefulness and computer self-efficacy affecting the behavioral intentions reading coaches have toward using a technology data tool. Subjective norms also demonstrated significant, strong and positive correlations for impacting reading coaches' behavioral intentions toward using a data technology tool in Test 2. Perceived ease of use did not affect behavioral intentions in either Test 1 or Test 2, as both p values determined a failure to reject the null hypothesis.

For middle school reading coaches the variables that correlated to the highest significant degree to behavioral intentions were perceived usefulness and computer self-efficacy.

The R-Squared values for perceived usefulness, computer self-efficacy, and subjective norms (for Test 2) all demonstrated high percentages that influence behavioral intentions. Perceived usefulness revealed over a 70% prediction percentage when correlated with behavioral intentions.

Table 11

Test 1: Middle School Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	16	.842** (L)	71%	.000	Reject
Perceived Ease of Use	16	.071 (NC)	1%	.795	Fail to Reject
Computer Self-Efficacy	16	.512* (L)	26%	.043	Reject
Subjective Norms	16	.488 (M)	24%	.055	Fail to Reject

**Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

Table 12

Test 2: Middle School Reading Coaches: Pearson's Correlation Matrix-Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	16	.861** (L)	74%	.000	Reject
Perceived Ease of Use	16	.150 (S)	2%	.578	Fail to Reject
Computer Self-Efficacy	16	.591* (L)	35%	.016	Reject
Subjective Norms	16	.591 (L)	35%	.016	Reject

** Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

For high school reading coaches, all variables including perceived usefulness, perceived ease of use, computer self-efficacy, and subjective norms generated statistics that indicate each variable did not affect high school reading coaches' behavioral intentions to use a data technology tool in both Tests One and Two. Failure to reject the null hypothesis in each case showed that the variables tested do not impact the behavioral intentions high school reading coaches have towards using a data technology tool with teachers, and in fact there were even medium, negative correlations for both tests when examining the relationship between subjective norms and their effect on behavioral intentions. Since the Likert Scale mean and median for high school reading coaches having behavioral intentions to use a data technology teacher were

high, there is a question as to what unknown variable(s) do impact their likelihood to have behavioral intentions to use a data technology tool.

Table 13

Test 1: High School Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	13	.429 (M)	18%	.144	Fail to Reject
Perceived Ease of Use	13	.211 (S)	4%	.489	Fail to Reject
Computer Self-Efficacy	13	.396 (M)	16%	.180	Fail to Reject
Subjective Norms	13	-.367 (M)	13%	.217	Fail to Reject

Table 14

Test 2: High School Reading Coaches: Pearson's Correlations between Perceived Usefulness, Perceived Ease of Use, Computer Self-Efficacy, and Subjective Norms to Behavioral Intentions

Variables	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
Perceived Usefulness	13	.494 (M)	24%	.086	Fail to Reject
Perceived Ease of Use	13	.124 (S)	2%	.688	Fail to Reject
Computer Self-Efficacy	13	.235 (S)	6%	.439	Fail to Reject
Subjective Norms	13	-.354 (M)	13%	.236	Fail to Reject

The hypothesis that: Reading coaches utilize data technology tools with classroom teachers based on different behavioral variables, is indicated to be true by the data results. The behavioral variables, including perceived usefulness, perceived ease of use, computer self-efficacy, and subjective norms, all vary in their levels of influence or non-influence on the behavioral intentions reading coaches have toward using a data technology tool. When analyzing what influences reading coaches' behavioral intentions it is important not to generalize what variables may impact behavioral intentions of all reading coaches together because when looking at the reading coaches by their levels (elementary, middle, and high), different behavioral variables show varying influence on behavioral intentions. For example, the data shows that middle school reading coaches demonstrated a remarkably higher likelihood to have behavioral intentions to use a data technology tool if they think the tool is going to be useful than

elementary and high school reading coaches. Also, the behavioral intentions of elementary school reading coaches showed that perceived ease of use impacted their behavioral intentions to a statistically large degree in contrast to both middle and high school reading coaches whose behavioral intentions were not impacted by perceived ease of use. Additionally, both elementary and middle school reading coaches showed a statistically significant correlation between computer self-efficacy and behavioral intentions compared to high school reading coaches who did not show a correlation between the two variables. Furthermore, high school reading coaches' results showed that none of the tested variables can be used to predict whether they will have behavioral intentions to use a data technology tool.

Overall, the data provided insight into what variables predict or do not predict behavioral intentions and how specific variables, when combined, can dramatically increase the prediction of variables positively affecting behavioral intentions. Furthermore, the data showed that there are varying degrees that a variable impacts behavioral intentions.

Research Question Three

Research question three: Is there a relationship between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers reflected identically at the elementary, middle, and high school levels? To answer the question Pearson's correlations were run using Test 1 data to correlate independent and dependent variables; discussions of the correlations are guided by the data results. Test 2 data was not generated because behavioral intention scores would be the same, as the same two item stems were used in Test 1 and Test 2 for behavioral intentions.

In examining the data using Pearson's correlation, correlations were determined with all reading coaches, elementary school reading coaches, middle school reading coaches, and high school reading coaches. Guidance was used from Cohen and Manion (1994) to analyze Pearson's correlations and is illustrated in Table 15. The farther the Pearson's correlation from zero, either positive or negative, the stronger the relationship between variables (Vaughnan, 2001).

Table 15

Interpretation Guide for Rating the Correlations

Correlation Range	Interpretation
Less than 0.10	No Correlation (NC)
0.10-0.29	Small (S)
0.30-0.49	Medium (M)
0.50+	Large (L)

Using Pearson's correlation, the years as an educator was correlated to behavioral intentions. These correlations are represented for all reading coaches in Table 16, for elementary school reading coaches in Table 17, for middle school reading coaches in Table 18, and for high school reading coaches in Table 19.

For all reading coaches who have been educators for 11-20 years, the data generated showed that years as an educator does influence their behavioral intentions to use a data technology tool. For educators who have 11-20 years of experience, there was a positive, small statistically significant correlation and the null hypothesis was rejected.

Table 16

All Reading Coaches: Years as an Educator Correlations

Years as an Educator	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-5 years	1	.016 (S)	0%	.902	Fail to Reject
6-10 years	13	-.219 (S)	5%	.090	Fail to Reject
11-20 years	24	.254* (S)	6%	.049	Reject
21+ years	24	-.075 (NC)	1%	.568	Fail to Reject

*Correlation is significant at the 0.05 level (2-tailed).

Elementary school reading coaches' data demonstrated that years as an educator does not influence their behavioral intentions to use a technology data tool as indicated by the failure to reject the null hypothesis in each case.

Table 17

Elementary School Reading Coaches: Years as an Educator Correlations

Years as an Educator	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-5 years	1	-.029 (NC)	0%	.876	Fail to Reject
6-10 years	7	.001 (NC)	0%	.994	Fail to Reject
11-20 years	9	.177 (S)	3%	.332	Fail to Reject
21+ years	15	-.151 (S)	2%	.411	Fail to Reject

Middle school reading coaches' data demonstrated that years as an educator does not influence their behavioral intentions to use a technology data tool as indicated by the failure to reject the null hypothesis in each case.

Table 18

Middle School Reading Coaches: Years as an Educator Correlations

Years as an Educator	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-5 years	0	-	-	-	-
6-10 years	4	-.271 (S)	7%	.272	Fail to Reject
11-20 years	7	.334 (M)	11%	.358	Fail to Reject
21+ years	5	-.105 (S)	1%	.971	Fail to Reject

High school reading coaches demonstrated that years as an educator influenced their behavioral intentions towards using a data technology tool in two areas. The null hypotheses were rejected for reading coaches who have been educators for 6-10 years and those who have been educators for 11-12 years only. High school reading coaches who have been educators for 6-10 years demonstrated a large negative statistically significant correlation between their years and their likelihood for having behavioral intentions to use a data technology tool. Conversely, high school reading coaches who have been educators for 11-20 years showed a large positive statistically significant correlation between their years and their likelihood for having behavioral intentions to use a data technology tool. The statistically significant positive finding for high school reading coaches that have been educators for 11-20 years was also reflected to a smaller degree when looking at all reading coaches, but not reflected for either elementary school reading coaches nor middle school reading coaches. For high school reading coaches who have been educators for 21+ years, there was no correlation found between their years and behavioral intentions towards using a data technology tool.

Table 19

High School Reading Coaches: Years as an Educator Correlations

Years as an Educator	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-5 years	0	-	-	-	-
6-10 years	2	-.706** (L)	50%	.007	Reject
11-20 years	8	.666* (L)	44%	.013	Reject
21+ years	3	-.165 (S)	3%	.589	Fail to Reject

**Correlation is significant at the 0.01 level (two-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

Using Pearson's correlation, the years in current role was correlated to behavioral intentions. These correlations are represented for all reading coaches in Table 20, for elementary school reading coaches in Table 21, for middle school reading coaches in Table 22, and for high school reading coaches in Table 23.

Pearson's correlation found no correlation for all reading coaches between time in their current role and behavioral intentions. Additionally there was a failure to reject the null hypothesis for each case examined.

Table 20

All Reading Coaches: Years in Current Role Correlations

Years in Current Role	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-2 years	24	-.002 (NC)	0%	.804	Fail to Reject
3-5 years	19	-.086 (NC)	1%	.358	Fail to Reject
6-8 years	9	.056 (NC)	0%	.828	Fail to Reject
9+ years	4	.086 (NC)	1%	.442	Fail to Reject

Pearson's correlation found no correlation for elementary school reading coaches between time in their current role and behavioral intentions. Also, the null hypothesis failed to reject each case examined.

Table 21

Elementary School Reading Coaches: Years in Current Role Correlations

Time in Current Role	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-2 years	15	-.044 (NC)	0%	.813	Fail to Reject
3-5 years	8	-.093 (NC)	1%	.614	Fail to Reject
6-8 years	3	.071 (NC)	1%	.701	Fail to Reject
9+ years	3	.071 (NC)	1%	.701	Fail to Reject

Pearson's correlation found no correlation for middle school reading coaches between time in their current role and behavioral intentions. Additionally, the null hypothesis indicated a failure to reject each case based on p values.

Table 22

Middle School Reading Coaches: Years in Current Role Correlations

Time in Current Role	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-2 years	5	-.190 (S)	4%	.403	Fail to Reject
3-5 years	7	.334 (M)	11%	.133	Fail to Reject
6-8 years	3	-.275 (S)	8%	.277	Fail to Reject
9+ years	0	-	-	-	-

Pearson's correlation found no correlation for high school reading coaches between time in their current role and behavioral intentions. For high school reading coaches the p values indicated a failure to reject the null hypothesis in each case analyzed.

Table 23

High School Reading Coaches: Years in Current Role Correlations

Time in Current Role	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
0-2 years	4	.182 (S)	3%	.552	Fail to Reject
3-5 years	3	-.536 (H)	29%	.059	Fail to Reject
6-8 years	3	.353 (M)	12%	.236	Fail to Reject
9+ years	1	.108 (S)	1%	.725	Fail to Reject

Using Pearson's correlation, reading education background of reading coaches was correlated to behavioral intentions. These correlations are represented for all reading coaches in Table 24, for elementary school reading coaches in Table 25, for middle school reading coaches in Table 26, and for high school reading coaches in Table 27.

For all reading coaches there was no correlation between behavioral intentions towards using a data technology tool and reading background according to Pearson's correlation. Furthermore, there was a failure to reject the null hypothesis based on p values for each correlation.

Table 24

All Reading Coaches: Reading Education Correlations

Reading Education Background	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
RC	9	-.081 (NC)	1%	.617	Fail to Reject
RE	36	-.117 (S)	1%	.340	Fail to Reject
WTRE	15	.176 (S)	3%	.196	Fail to Reject
WTRC	1	.010 (NC)	0%	.902	Fail to Reject
NRB	1	.074 (NC)	1%	.532	Fail to Reject

RC=Reading Certification

RE=Reading Endorsement

WTRE=Working Towards Reading Endorsement

WTRC=Working Towards Reading Certification

NRB=No Reading Background

For elementary reading coaches there was no correlation between behavioral intentions towards using a data technology tool and reading background according to Pearson's correlation. Additionally, p values provided information to fail to reject the null hypothesis in each case analyzed.

Table 25

Elementary School Reading Coaches: Reading Education Correlations

Reading Education Background	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
RC	4	.155 (S)	2%	.397	Fail to Reject
RE	15	-.115 (S)	2%	.531	Fail to Reject
WTRE	12	-.014 (NC)	0%	.940	Fail to Reject
WTRC	0	-	-	-	-
NRB	1	.074 (NC)	1%	.689	Fail to Reject

RC=Reading Certification

RE=Reading Endorsement

WTRE=Working Towards Reading Endorsement

WTRC=Working Towards Reading Certification-None Working on It

NRB=No Reading Background

For middle school reading coaches there was no correlation between behavioral intentions towards using a data technology tool and reading background according to Pearson's correlation. P values also provided information to fail to reject the null hypothesis in each correlation examined.

Table 26

Middle School Reading Coaches: Reading Education Correlations

Reading Education Background	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
RC	4	-.451 (M)	20%	.073	Fail to Reject
RE	11	.358 (M)	13%	.146	Fail to Reject
WTRE	1	.121 (S)	1%	.731	Fail to Reject
WTRC	0	-	-	-	-
NRB	0	-	-	-	-

RC=Reading Certification

RE=Reading Endorsement

WTRE=Working Towards Reading Endorsement

WTRC=Working Towards Reading Certification

NRB=No Reading Background

For high school reading coaches there was no correlation between behavioral intentions towards using a data technology tool and reading background according to Pearson's correlation. The p values indicated that each instance examined that there was a failure to reject the null hypotheses.

Table 27

High School Reading Coaches: Reading Education Correlations

Reading Education Background	n	Behavioral Intentions (r)	R-Squared	p	Null Hypothesis
RC	1	-.009 (NC)	0%	.977	Fail to Reject
RE	9	-.317 (M)	10%	.291	Fail to Reject
WTRE	2	.333 (M)	11%	.267	Fail to Reject
WTRC	1	.108 (S)	1%	.725	Fail to Reject
NRB	0	-	-	-	-

RC=Reading Certification

RE=Reading Endorsement

WTRE=Working Towards Reading Endorsement

WTRC=Working Towards Reading Certification

NRB=No Reading Background

The hypothesis is supported by the data analyzed: There is a difference in the relationships between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers for elementary, middle and high levels. To explain this answer, demographic information, including years as an educator, years in their current role, and reading background, were correlated to behavioral intentions. Although in most cases there was no correlation between independent variables and behavioral intentions, there were two areas for high school coaches that showed statistically significant information. High school coaches who have taught 6-10 years showed a statistically significant negative and large correlation between their years as an educator and their behavioral intentions to use a data technology tool, while those who have taught for 11-20 years showed the opposite; a significantly positive and large correlation between their years as an educator and their behavioral intentions to use a data technology tool. For both of these instances, there was a failure to reject the null hypotheses

indicating a positive or negative, respectfully, influence on years as an educator predicting the use or not predicting the use of utilizing a data technology tool.

Research Question Four

Research question four: What are reading coaches thoughts on using data technology tools? To learn the thoughts of reading coaches, they were asked: From your perspective as a reading coach or reading contact, what would you like the researcher to know about using data tools in helping teachers? The responses to the question were categorized and created trends. Thirty-seven out of sixty-one, or approximately 61%, of the coaches responded to the qualitative question in the survey.

The trends in the qualitative question strongly predicted assumptions of the hypothesis that: Reading coaches will have similar opinions regarding their intentions to use technology tools with teachers. Overall, three trends emerged from the data indicating the reading coaches believe that support in the form of trainings is needed for educators, data technology tools are useful, and technology tools need to be user-friendly.

In analyzing the data, approximately 24% of the respondents or 16% of the total population of the coaches believe that educators need support in the form of trainings in using data technology tools. Some comments included they “Need ongoing training to share with other teachers,” and “The support from the district enables me to use it more effectively.” Two individuals wrote that hands-on training is important when it comes to training educators in how to use and implement a data technology tool. Finally, one response really explained this trend well, “We have to be properly trained on using the tools before we are expected to use them and teach others to use them.”

Additionally, approximately 19% of the respondents or 11% of the total population reported that they believe data technology tools are useful. One noted a data tool, “makes a teacher's job more manageable and saves time in planning for student instruction,” while another commented, “I think that data tools are extremely helpful in reviewing the data to guide instruction. It helps to make data analysis more manageable.” Finally, one educator summed it up best by stating, “Yes, I believe that using data tools in helping teachers is extremely important.”

Finally, 32% of the respondents or 20% of the total population indicated that the data technology tools need to be user-friendly. Comments that helped shape this trend included “Data tools need to be user- friendly and help the classroom teachers/coaches use time wisely,” and “Keep them user-friendly; time is always an issue.” One summed it up as, “Teachers are so overwhelmed with day to day work that anything we can do to help simplify the data collection and analysis process will help streamline their jobs.” One final comment that also helped give a picture of the need for user-friendly tools is noted in this response, “They should be very easy to access and provide instructional implications with data read out.”

These trends indicate that the hypothesis: Reading coaches will have similar opinions regarding the utilization of data technology tools with teacher, is correct.

Summary

The results of the analysis based on the hypotheses tested can be summarized as follows:

1. Reading coaches have specific behavioral intentions when utilizing a data technology tool with classroom teachers.

2. Reading coaches utilize a data technology tool with classroom teachers based on different behavioral variables.
3. There were significant differences amongst the relationships between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers which were not reflected identically at the elementary, middle, and high school grade levels.
4. Qualitative data supported the assertion that reading coaches did hold similar opinions regarding the utilization of data technology tools with teachers.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

The purpose of this chapter is to report the conclusions based on the findings in the research and the recommendations emanating from this study. These are organized into three sections dealing with: 1) the conclusions of the research based on the findings, 2) a discussion of the conclusions and 3) recommendations emerging from the study.

Conclusions

The conclusions, based on the findings of this investigation, are as follows: 1) The research hypothesis, which stated that: Reading coaches have specific behavioral intentions when utilizing a data technology tool with classroom teachers, was supported by the data. 2) The research hypothesis, which stated that: Reading coaches utilize a data technology tool with classroom teachers based on different behavioral variables, was supported by the data. 3) The research hypothesis, which stated that: There is a difference in the relationships between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers for elementary, middle, and high school levels, was supported by the data. 4) The research hypothesis, which stated that: Reading coaches will have similar opinions regarding the utilization of data technology tools with teachers, was also supported by the data.

Discussion of the Conclusions

In examining the findings, at least four rival explanations compete with the research hypotheses in the context of this research. The threats to either the internal or external validity of the data presented and discussed include: mortality, Hawthorne effect, measurement of the dependent variable, and statistical regression.

First, it is possible that the data may have been influenced by an internal validity threat referred to by Campbell and Stanley (1963) as "mortality". That is, reading coaches either have left the school system or came into the school system in a pattern that might produce differences in the data. To diminish the possibility of mortality, the first question in the survey was used as a determinant for indicating if the coaches had viewed the tool being studied. The data of any coach who had not viewed the tool were immediately eliminated and not calculated into the results. This action of deleting coaches whose data were invalid relates to mortality because only reading coaches who have been in the school system long enough to have had exposure to the tool would have been calculated into the results.

Second, it is possible that the overall high behavioral intentions of reading coaches in using a data technology tool with teachers demonstrates a case of what Bracht and Glass (1968) call the "Hawthorne effect," a threat to the external validity of the study. This explanation is proposed because the reading coaches may assume that district personnel or their "bosses" may be interested in determining if they are fulfilling an expectation of their job role in using the tools provided to them for the intention of utilizing data with teachers that can impact student achievement. In this case reading coaches could feel as though their job performances are being monitored and falsely indicate a high level of behavioral intentions to use a data technology tool, provided by the district, with teachers. Thus indicating higher productivity in their job role than what is actually occurring. Although, the Hawthorne effect may explain how reading coaches responded with such high behavioral intentions to use the data technology tool with teachers, this effect is not likely applicable in this case as an explanation for the data results because the survey was anonymous and all participants were informed that the survey was anonymous and not

mandatory. Thus, there is no reason to doubt the conclusion that all reading coaches have high behavioral intentions to use a data technology tool with teachers.

Third, the “measurement of the dependent variable” may be a considered an external validity threat to the data yielded in this study (Bracht & Glass, 1968). The measurement of the dependent variable as reported by Bracht and Glass (1968) is considered because an instrument used, in this case the BI Survey, may not accurately measure the variables tested. Although this threat may be taken into consideration when examining the results, it is not likely to be an explanation for the data results. The reason it is not likely to be an explanation of the data results is because content validity and construct validity of the item stems used in the BI Survey were established based on the research articles of Davis (1989), Venkatesh and Davis (2000), and Venkatesh (2000). For the creation of the BI Survey each item stem was either kept the same or only minimally modified to be applicable for the tool being used in the study, with the permission of both Venkatesh and Davis. Another reason the measurement of the dependent variable threat is not a likely explanation for the results is because the BI Survey was previously piloted with secondary reading coaches in a large urban Florida school district and in that case the reliability indicators using Cronbach’s Alpha ranged from .752 to .956. Nunnally and Bernstein (1994) have indicated that a Cronbach’s Alpha score of more than .70 indicates a reasonable relationship or measure amongst variables. For this survey, the Cronbach’s Alpha scores were also high, ranging from .790 to .944.

Fourth, “statistical regression” may be a considered threat to the internal validity of this study as reported by Cook and Campbell (1979). This threat takes into consideration that data will move towards the mean and in this case, that may have yielded higher mean scores when

examining the Likert Scale scores that were used to determine reading coaches' behavioral intentions towards using a data technology tool. Perhaps this threat seems to have merit, except that the median scores were also reported for each level (elementary, middle, and high) and for all reading coaches which indicated in each instance a median score of four, a high indicator for having behavioral intentions to utilize the tool with teachers. This alternative way of looking at the data is a second verifying factor that the behavioral intentions are high for all reading coaches and even when examining them according to their levels.

Implications for Practice

The first finding that all reading coaches and reading coaches when examined by levels (elementary, middle, and high) have very good behavioral intentions towards utilizing a data technology tool with teachers is valuable to learn. The finding is especially important since research indicates that reading coaches have a crucial role in helping teachers understand and utilize their student data to tailor instruction to the needs of students (Walpole & Blamey, 2008). The need for data technology tools seems apparent as they can be helpful in quickly organizing, information in usable ways for the benefit of providing teachers with usable instruction designed for the specific needs a student may have. An issue of time was brought to the forefront by Miller (2009) whose research indicated that reading coaches do not feel they have enough time to do their jobs and Marsh et al. (2008) who recommended that administrators and policy makers help reading coaches find more time to spend on their role of being in the classroom. This time issue may be alleviated to some degree by the use of data technology tools that can more quickly crunch data and formulate instructional plans than the hours and days it may take educators to do so on their own. The time factor is important in another way because assessment

data needs to be used quickly to help students, data technology tools would most likely be the fastest way to determine instructional needs that can be implemented more immediately than when educators try to interpret, analyze, trend out, record for progress monitoring, and use data on their own. It is apparent that data technology tools are on the rise by the millions of federal dollars spent on providing them to school districts as a way to help impact and monitor student achievement. Furthermore, it is very promising that reading coaches are ready to take on their role in helping teachers use technology data tools for the benefit of student achievement (Mandinach et al., 2006). The use of a data tool can allow reading coaches to determine which teachers need more resource allocation to assist students based on student data and trends in data (Pinkus, 2009). The finding that reading coaches have good behavioral intentions to use a data technology tool contradicts the research by Hu et al. (2003) that public school teachers are technology resistant, considering that reading coaches are usually former teachers (Sturtevant, 2003).

The second finding that reading coaches utilize data technology tools with classroom teachers based on different behavioral variables is especially insightful in providing guidance on the kind of professional development reading coaches should receive. Just like our students, a one size fits all approach to the kind of professional development reading coaches may be receiving does not seem like it would make sense in light of the results of the study indicated that reading coaches are influenced by different behavioral variables. The idea of providing reading coaches with differentiated professional development as suggested by Blachowicz et al. (2010) seems like a logical approach. For example, the study revealed that computer self-efficacy plays a critical factor in determining the behavioral intentions elementary and middle school reading

coaches have toward using a data technology tool with teachers and so it seems like addressing their data technology skills by providing on-going trainings, support, and practice would be helpful in increasing the likelihood that the reading coaches use a data technology tool with teachers. Data tool “field trips” could be devised to take the reading coaches through a process of experimenting with their school data in an actual tool in order to gain comfort and familiarity with utilizing a tool so that they are more willing to use it with others. The field trips could be designed for “beginner” “intermediate” and “advanced” levels so that reading coaches could enter in to where they think they need to grow from and continue to develop. It would be beneficial if the reading coaches have a tool expert at their disposal while experimenting with the tools in the event support and encouragement is needed. The data tool expert could be a well-trained reading coach or a district reading specialist.

Since elementary reading coaches have higher behavioral intentions based on the perceived ease of use of a tool, it seems as though the field trip idea would also provide them with an opportunity to use a tool and gain more ease of use with the practice provided by the “field trip” activities.

The results of the study also showed that variables in combination have a greater percent likelihood of impacting behavioral intentions and so providing reading coaches with opportunities to enhance variables together may provide especially impactful professional development. For example, video demonstrations of how to use a tool may also provide reading coaches with a way to revisit information and help improve their computer self-efficacy skills and perceived ease of use regarding a tool. The benefit of video demonstrations and field trips are that the reading coaches may also use these teaching vehicles when educating their teachers

in how to use the tools, thus building teacher capacity. Finally, these tactics of providing reading coaches with teaching tools to help teachers use data technology tools may provide entry points to work with teachers more on their data and enrich data discussions and student achievement since the research provided by Marsh et al. (2008) indicated that student achievement was highest in schools where teachers are spending time with reading coaches in devising ways to use student assessment data.

The third finding that there is a difference in the relationships between reading coaches' behavioral intentions and utilization of a data technology tool with classroom teachers for elementary, middle, and high levels is another important discovery. The data reflected that all reading coaches who have been educators for 11-20 years showed a small positive statistically significant relationship to behavioral intentions; however that positive statistically significant relationship was only further evident when examining high school reading coaches. The study showed that high school reading coaches who have been educators for 11-20 years have the only large positive statistically significant correlation to behavioral intentions. Since these individuals seem the most likely to use a data technology tool with reading coaches it may be important to consider recruiting them to be data technology experts who provide support to other reading coaches in using data technology tools, promoting leadership opportunities for this group. This group may be able to positively influence others to use a data technology tool by providing short testimonials to others as well. Since high school reading coaches who have been educators for 6-10 years indicated a strong negative correlation with behavioral intentions, it may be advisable for a researcher to seek out why this may be by conducting interviews or a focus group. That other demographics for all other groups not mentioned did not show a correlation between their

demographics and behavioral intentions, these ideas may not need to be considered when creating professional development for those reading coaches.

The fourth finding that reading coaches do hold similar opinions regarding the utilization of data tool with teachers is important to consider when districts or policy makers are considering buying or creating technology data tools, when districts or policy makers are considering how to launch a data technology tool, and when districts and policy makers are determining how to set up professional development in using a data technology tool. The trends in the study showed that reading coaches feel that data technology tools are useful, but need to be user-friendly. Another trend noted is that reading coaches also felt that on-going professional development is key to the success of using a data technology tool.

Thus, when districts and policy makers are looking to adopt or create a data technology tool, it may be to their benefit to include reading coaches in their discussions and evaluations of tools. Reading coaches could be studied by districts and policy makers using a “think-aloud” process where they share their thoughts while engaged with a data technology tool they are trying out. The “think-aloud” technique may provide valuable information as to whether to adopt or not adopt a tool or in planning how to create a tool.

Additionally, when districts or policy makers are considering how to launch a tool they may want to make it clear how a data technology tool is user-friendly which may improve the way the tool is accepted and used by reading coaches and teachers. This may involve recruiting reading coaches to try out the data technology tools and report back to other reading coaches their positive experiences. Since subjective norms only impacted elementary reading coaches behavioral intentions, it may be wise for districts and policy makers to have district support

personal or administrators be the ones who share their endorsement of using a data technology tool in addition to having reading coaches provide positive testimonials when launching a data technology tool. For middle school and high school reading coaches it may not matter if district support personal or administrators share their endorsement of using a data technology tool, but they may be influenced by other reading coaches' testimonials.

Importantly, when districts and policy makers are determining how to set up professional development in using a data technology tool it seems crucial that they consider the variables presented in this study, including computer self-efficacy, perceived ease of use, and perceived usefulness when creating professional development. As previously mentioned, differentiated instruction based on the ways coaches at different levels are impacted by the studied variables may be a great way to impact reading coaches behavioral intentions towards using a data technology tool. It may also be beneficial to provide reading coaches with choices about what kind of professional development to attend in cultivating their behavioral intentions. For example, some coaches may be motivated to use a data technology tool with others if they hear from other coaches experiences in using data technology tools with teachers in a "what I've learned so far" kind of workshop. In this workshop reading coaches could share what worked or didn't work in helping teachers use a data technology tool. Also, on-going monthly professional development sessions that provide updates on tools and successes may also be impactful. Furthermore, the previously presented "field trip" activity may be helpful for reading coaches and offered during each monthly reading coach professional development meeting.

Additionally, it may be wise for districts to consider allowing reading coaches to occasionally bring another individual from their school along to also experience the professional

development so that a reading coach has a support teacher or administrator on location.

Administrators would also benefit from being invited to any reading coach meeting session so that they also can be aware of technology tools and be supportive to their reading coaches.

Finally, results of this research may have implications for the employment of reading coaches as districts and schools may want to consider hiring reading coaches who have experiences in utilizing technology tools, such as Excel or other tools. Policy makers could provide web seminars for individuals interested in becoming reading coaches that teach individuals the basics of how to use certain technology tools that may be prevalent in a state or district. These webinars could be a part of district requirements for potential reading coaches. Districts could create pools of qualified reading coaches for schools to choose from and taking data trainings may be a prerequisite if it is set up through the district. Universities that provide reading endorsement or reading certification could also add in seminars to their classes that bolster data technology skills for pre-services teachers so that they are more highly qualified as teachers or future reading coaches when they graduate.

Recommendations for Future Research

1. This study should be replicated in rural school settings.
2. While reasons why some reading coaches work harder than others were not a concern of this study, research in this area is warranted.
3. Other variables need to be explored to explain why high school reading coaches' behavioral intentions were not impacted by perceived ease of use, perceived usefulness, computer self-efficacy, nor subjective norms.

4. A recommendation for further studies related to this topic is for researchers to add more instruments to the survey, such as an actual use variable. The actual use variable would be valuable to compare in deciding how other variables such as perceived usefulness and computer self-efficacy predicted actual use of a technology tool.

APPENDIX A
IRB LETTER OF PERMISSION FOR HUMAN SUBJECTS



University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Cherie A. Behrens**

Date: **November 08, 2011**

Dear Researcher:

On 11/8/2011, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review: UCF Initial Review Submission Form
Project Title: The Relationship Between Reading Coaches' Utilization of Data
Technology and Teacher Development
Investigator: Cherie A. Behrens
IRB Number: SBE-11-07997
Funding Agency: None

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Janice Turchin on 11/08/2011 04:49:51 PM EST

A handwritten signature in black ink that reads "Janice Turchin".

IRB Coordinator

APPENDIX B
BEHAVIORAL INTENTIONS SURVEY

Behavioral Intentions Survey

Please Note-District identifying information has been blocked with a [REDACTED] symbol.

Determinant for Verification of Exposure to the Tool

1. Have you viewed the [REDACTED] Teacher Progress Monitoring Tool for FAIR?

- ☐ Yes
☐ No

Perceived Usefulness

2. Please indicate your degree of agreement or disagreement of the following statements:
Using the [REDACTED] Teacher Progress Monitoring Tool for FAIR...

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	I Do Not Know
enables teachers to quickly utilize FAIR data.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
improves teacher job performance.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
makes a teacher's job more manageable.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
saves time in planning for student instruction.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Perceived Ease of Use

3. Please indicate your degree of agreement or disagreement of the following statements in regards to the [REDACTED] Teacher Progress Monitoring Tool for FAIR:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	I Do Not Know
Learning to use the Excel tool is easy for me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I find it easy to get the tool to do what I want it to do.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
It is clear to me how to use the tool.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I understand how to interact with the tool.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Computer Self-Efficacy

4. Please indicate your degree of agreement or disagreement of the following statements:
I could use the [redacted] Teacher Progress Monitoring Tool for FAIR if...

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	I Do Not Know
I had seen someone else using the tool.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I viewed the tutorial for using the tool.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I had practice using the tool while able to obtain assistance when needed.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I could call or email someone for assistance if I got stuck.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
someone showed me how to use it.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I was left alone to interact with it.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Subjective Norms

5. Please indicate your degree of agreement or disagreement of the following statements in regards to the [redacted] Teacher Progress Monitoring Tool for FAIR:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	I Do Not Know
If others, at other schools, use the tool I am more likely to use it	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If administrators suggest using the tool I am more likely to use it	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If the district promotes using the tool I am more likely to use it	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Behavioral Intentions

6. Please indicate your degree of agreement or disagreement of the following statements:
If I have access to the [REDACTED] Teacher Progress Monitoring Tool for FAIR then...

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	I Do Not Know
I predict I will use this tool in the future	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I predict that I will show others how to use it in the future	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Demographics

7. Please indicate how long you have been an educator.

- ☐ 0-5 years
- ☐ 6-10 years
- ☐ 11-20 years
- ☐ 21+ years

8. Please indicate your reading background.

- ☐ I have reading certification
- ☐ I have reading endorsement
- ☐ I am working towards reading endorsement
- ☐ I am working towards reading certification
- ☐ None of the above

9. Please select what school level you work at currently. If you serve multiple levels, please select the level you mostly serve at your school site.

- ☐ Elementary
- ☐ Middle
- ☐ High

10. Please indicate how long you have been in your current role as a reading coach or reading contact.

Qualitative Question

11. From your perspective as a reading coach or reading contact, what would you like the researcher to know about using data tools in helping teachers?

APPENDIX C
BI SURVEY ITEMS USED FOR RELIABILITY TESTING

BI SURVEY ITEMS USED FOR RELIABILITY TESTING

<p>Perceived Usefulness</p> <p>Prompt: Using the [redacted] Teacher Progress Monitoring Tool for FAIR...</p> <ol style="list-style-type: none"> enables teachers to quickly utilize FAIR data. improves teacher job performance. makes a teacher's job more manageable. saves time in planning for student instruction. 	<p>Test 1 Cronbach's Alpha=.871</p> <p>Includes stems: 2,3, and 4</p>	<p>Test 2 Cronbach's Alpha=.867</p> <p>Includes stems: 1, 2,3, and 4</p>
<p>Perceived Ease of Use</p> <p>Prompt: Please indicate your degree of agreement or disagreement of the following statements in regards to the [redacted] Teacher Progress Monitoring Tool for FAIR:</p> <ol style="list-style-type: none"> Learning to use the Excel tool is easy for me. I find it easy to get the tool to do what I want it to do. It is clear to me how to use the tool. I understand how to interact with the tool. 	<p>Test 1 Cronbach's Alpha=.906</p> <p>Includes stems: 1, 2, 3, and 4</p>	<p>Test 2 Cronbach's Alpha=.901</p> <p>Includes stems: 2, 3, and 4</p>
<p>Computer Self-Efficacy</p> <p>Prompt: I could use the [redacted] Teacher Progress Monitoring Tool for FAIR if...</p> <ol style="list-style-type: none"> I had seen some else using the tool. I viewed the tutorial for using the tool. I had practice using the tool while able to obtain assistance when needed. If I could call or email someone for assistance if I got stuck. if someone showed me how to use it if I was left alone to interact with it. 	<p>Test 1 Cronbach's Alpha=.803</p> <p>Includes stems: 1,2,3,4, and 5</p>	<p>Test 2 Cronbach's Alpha=.790</p> <p>Includes stems: 3,4, and 5</p>
<p>Subjective Norms</p> <p>Prompt: Please indicate your degree of agreement or disagreement of the following statements in regards to the [redacted] Teacher Progress Monitoring Tool for FAIR:</p> <ol style="list-style-type: none"> If others, at other schools, use the tool I am more likely to use it. If administrators suggest using the tool I am more likely to use it. If the district promotes using the tool I am more likely to use it. 	<p>Test 1 Cronbach's Alpha=.892</p> <p>Includes stems: 2 and 3</p>	<p>Test 2 Cronbach's Alpha=.832</p> <p>Includes stems: 1, 2, and 3</p>
<p>Behavioral Intentions</p> <p>Prompt: If I have access to the [redacted] Teacher Progress Monitoring Tool for FAIR then...</p> <ol style="list-style-type: none"> I predict I will use this tool in the future. I predict that I will show others how to use it in the future. 	<p>Test 1 Cronbach's Alpha=.944</p> <p>Includes stems: 1 and 2</p>	<p>Test 2 Cronbach's Alpha=.944</p> <p>Includes stems: 1 and 2</p>

APPENDIX D
DAVIS PERMISSION LETTER

RE: Request: Permission to Use Your Work

From: **Fred Davis** (FDavis@walton.uark.edu)
Sent: Thu 9/22/11 1:31 AM
To: cherie.behrens@knights.ucf.edu (cherie.behrens@knights.ucf.edu)

Cherie

You have my permission to use the TAM measurement scales as long as you cite the articles you obtained them from in your written reports.

Best wishes

Fred D Davis

Distinguished Professor and David Glass Chair of Information Systems
Walton College of Business, University of Arkansas, Fayetteville, Arkansas, USA
Visiting Professor of Service Systems Management and Engineering
Sogang Business School, Sogang University, Seoul, Korea

fdavis@walton.uark.edu

From: cherie.behrens@knights.ucf.edu [cherie.behrens@knights.ucf.edu]
Sent: Thursday, September 22, 2011 10:43 AM
To: Fred Davis
Subject: Request: Permission to Use Your Work

Dear Dr. Davis,

First of all, thank you for inventing the Technology Acceptance Model. Currently, I am a doctoral student at the University of Central Florida and I am writing to you in order to request permission to use your work for the survey I would like to use for my dissertation study. I will cite your work. Some of the survey components also come from work that you accomplished with Dr. Venkatesh. I will also request his permission, in the same manner.

Attached is the survey I am referring to in this request.

Dr. Davis, thank you for considering this request. I think the implications of the study will contribute to the field of education.

Sincerely,

Cherie

Cherie Behrens
Visiting Instructor, School of Teaching, Learning and Leadership
College of Education
University of Central Florida
407-823-1869

APPENDIX E
VENKATESH PERMISSION LETTER

RE: Request: Permission to Use Your Work

From: **Viswanath Venkatesh** (vvenkatesh@vvenkatesh.us)
Sent: Thu 9/22/11 8:44 AM
To: cherie.behrens@knights.ucf.edu

You have my permission to adapt this work for your use.

Best wishes.

NEW BOOK RELEASED: AUGUST 2011

Road to Success: A Guide for Doctoral Students and Junior Faculty Members in the Behavioral and Social Sciences

BOOK CAN BE ORDERED AT: <http://vvenkatesh.com/book>

Sincerely,

Viswanath Venkatesh

Distinguished Professor and George and Boyce Billingsley Chair in Information Systems

Walton College of Business

University of Arkansas

Fayetteville, AR 72701

Phone: 479-575-3869; Fax: 479-575-3689

Email: vvenkatesh@vvenkatesh.us

Website: <http://vvenkatesh.com>

IS Research Rankings Website: <http://vvenkatesh.com/ISRanking>

From: cherie.behrens@knights.ucf.edu [mailto:cherie.behrens@knights.ucf.edu]
Sent: Wednesday, September 21, 2011 9:01 PM
To: vvenkatesh@vvenkatesh.us
Subject: Request: Permission to Use Your Work

Dear Dr. Venkatesh,

First of all, thank you for your work in developing the TAM2. Currently, I am a doctoral student at the University of Central Florida and I am writing to you in order to request permission to use your work for the survey I would like to use for my dissertation study. I will cite your work. Some of the survey components come from work that you accomplished with Dr. Davis. I will also request his permission, in the same manner.

Attached is the survey I am referring to in this request.

Dr. Venkatesh, thank you for considering this request. I think the implications of the study will contribute to the field of education.

Sincerely,

Cherie

Cherie Behrens
Visiting Instructor, School of Teaching, Learning and Leadership
College of Education
University of Central Florida
407-823-1869

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